Impact of Artificial Intelligence Adoption on External Auditing Efficiency in Deposit Money Banks in Nigeria: Evidence from Taraba State

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ABSTRACT

This research examined the impact of artificial intelligence adoption on external auditing efficiency in Deposit Money Banks in Taraba State, Nigeria, covering the period 2021 to 2025. Specifically, it assessed the effects of AI-based audit automation, machine learning analytics, and AI fraud detection systems on audit timeliness, accuracy, workload reduction, and fraud detection. Primary data were collected from external auditors, internal control officers, compliance officers, finance officers, and other audit-related personnel using structured questionnaires. Descriptive statistics, correlation analysis, and multiple regression analysis were employed to analyze the data. The findings reveal that all three AI adoption variables positively and significantly influence external auditing efficiency, with AI-based audit automation showing the strongest effect. The study concludes that integrating AI tools into audit processes enhances efficiency, reduces manual workload, and improves audit accuracy. Recommendations include investing in AI tools, building auditors' digital competence, strengthening regulatory guidance, and improving IT infrastructure. These findings provide practical insights for auditors, bank management, and regulators on the effective use of AI to improve audit performance.

Keywords: Artificial intelligence, external auditing efficiency, AI-based audit automation, machine learning analytics, AI fraud detection systems, Deposit Money Banks, Taraba State, Nigeria.

INTRODUCTION

The banking sector is among the most data-intensive sectors in the contemporary economy, producing significant quantities of transactional, operational, and financial data each day. This complexity presents considerable hurdles to external auditors, who are responsible for verifying the accuracy, completeness, and trustworthiness of financial accounts. The efficiency of external auditing defined as the capacity of auditors to conduct audits properly, promptly, and economically, continues to be a vital factor influencing audit quality and stakeholder trust (Kokina & Davenport, 2017). In Nigeria, Deposit Money Banks function within a rigorously regulated framework overseen by the Central Bank of Nigeria (CBN) and the Financial Reporting Council of Nigeria (FRCN), necessitating that auditors comply meticulously with auditing standards while handling escalating data volumes (CBN, 2023; FRCN, 2022).

Recent technological breakthroughs, especially in artificial intelligence (AI), have revolutionized the auditing domain by automating tedious processes, augmenting data analysis, and expanding fraud detection capabilities. AI applications, including AI-driven audit automation, machine learning analytics, and AI-facilitated fraud detection systems, possess considerable potential to augment auditing efficiency by diminishing manual labor, enhancing timeliness, and elevating the precision of audit evidence (Liu et al., 2021; Warren et al., 2015). Notwithstanding these opportunities, the adoption of AI in Nigerian Deposit Money Banks is inconsistent, and empirical data regarding its effect on external auditing efficiency at the state level is scarce, especially in under-researched areas such as Taraba State.

Several studies have underscored the capacity of AI to improve audit processes worldwide. Kokina and Davenport (2017) contend that AI can execute analytical tasks that are labor-intensive for human auditors, whereas machine learning models can detect anomalous patterns and probable fraud with greater accuracy. Brynjolfsson and McAfee (2017) note that digital technologies in auditing not only expedite regular activities but also enable auditors to concentrate on high-level judgment and risk evaluation. The incorporation of AI in auditing in Nigeria remains in its infancy, facing obstacles such as inadequate digital competencies among auditors, infrastructure limitations, and legislative ambiguities (Okafor et al., 2022).

In light of these dynamics, it is essential to experimentally examine the effect of AI adoption on the effectiveness of external auditing in Deposit Money Banks in Taraba State. This study aims to address the existing gap by investigating the impact of AI-driven audit automation, machine learning analytics, and AI fraud detection systems on auditing efficiency.

Statement of the Problem

Deposit Money Banks in Nigeria manage substantial financial transactions every day, hence enhancing the complexity of external audit engagements. Auditors encounter hurdles include prolonged audit completion, labor-intensive procedures, inaccuracies in financial reporting, and obstacles in fraud detection. These inefficiencies frequently result in extended audit cycles, increased operating expenses, and less trust in audited financial statements (Okafor et al., 2022; Kokina & Davenport, 2017).

Notwithstanding the capacity of artificial intelligence (AI) to improve audit procedures via automation, machine learning analytics, and fraud detection, its implementation in Nigerian institutions is still restricted and erratic, especially in under-researched areas such as Taraba State. Auditors in these banks frequently lack the requisite digital competencies and infrastructure necessary for the comprehensive integration of AI into audit processes, leading to ongoing inefficiencies (Liu et al., 2021).

Although previous research has explored AI in auditing at the national or organizational level, there is a lack of empirical information about the impact of AI adoption on external auditing efficiency in Deposit Money Banks at the state level. This disparity obstructs the creation of effective policies, impedes management decision-making, and complicates professional practices concerning AI integration in auditing. This study aims to examine the influence of AI-driven audit automation, machine learning analytics, and AI fraud detection systems on the efficacy of external audits in Deposit Money Banks in Taraba State, Nigeria.

Research Questions

This study seeks to answer the following research questions:

i. How does AI-based audit automation influence external auditing efficiency in Deposit Money Banks in Nigeria?
ii. What is the effect of machine learning analytics on external auditing efficiency in Deposit Money Banks in Nigeria?
iii. To what extent do AI fraud detection systems affect external auditing efficiency in Deposit Money Banks in Nigeria?

Objective of the Study

The main objective of this study is to examine the impact of artificial intelligence adoption on external auditing efficiency in Deposit Money Banks in Nigeria, using evidence from Taraba State. Other specific objectives that the study seeks to achieve are to:

i. examine the effect of AI-based audit automation on external auditing efficiency in Deposit Money Banks in Nigeria;

ii. determine the influence of machine learning analytics on external auditing efficiency in Deposit Money Banks in Nigeria; and
iii. assess the effect of AI fraud detection systems on external auditing efficiency in Deposit Money Banks in Nigeria.

Research Hypotheses

The following hypotheses will guide the study:

H01: AI-based audit automation has no significant effect on external auditing efficiency in Deposit Money Banks in Nigeria.

H02: Machine learning analytics has no significant effect on external auditing efficiency in Deposit Money Banks in Nigeria.

H03: AI fraud detection systems have no significant effect on external auditing efficiency in Deposit Money Banks in Nigeria.

Significance and Scope of the Study

This study is important as it offers practical, academic, and policy insights into the influence of artificial intelligence implementation on the effectiveness of external auditing in Deposit Money Banks in Taraba State, Nigeria. The findings will inform auditors, bank management, and regulators on the enhancement of audit timeliness, accuracy, and cost-effectiveness through AI-based audit automation, machine learning analytics, and AI fraud detection systems (Kokina & Davenport, 2017; Liu et al., 2021). The study fills a gap in empirical literature by offering state-level evidence on AI adoption and audit efficiency, thereby enhancing understanding of audit technology integration and establishing a basis for future research. The findings will guide regulatory entities, including the Financial Reporting Council of Nigeria (FRCN) and the Central Bank of Nigeria (CBN), in formulating effective strategies for AI implementation, encompassing the establishment of training programs, digital audit standards, and ethical guidelines.

This paper examines Deposit Money Banks in Taraba State from 2021 to 2025, analyzing AI-driven audit automation, machine learning analytics, and AI fraud detection technologies and their impact on the efficiency of external auditing. Data will be gathered from external auditors, internal control officers, and other audit-related staff within these banks to facilitate a focused research into the influence of AI on audit performance within the designated timeframe.

LITERATURE REVIEW

Concept of External Auditing Efficiency

External auditing efficiency refers to the capacity of external auditors to perform audits accurately, promptly, economically, and effectively in identifying errors or fraud, all while complying with professional auditing standards (Arens, Elder, & Beasley, 2020). Effective audits guarantee the reliability of financial statements, uphold stakeholder confidence, and fulfill regulatory obligations. Our comprehension of external auditing efficiency extends beyond the sheer swiftness of audit completion. It includes the quality and dependability of audit evidence, the minimization of manual labor, and the overall efficiency of audit procedures. Enhanced auditing efficiency allows auditors to concentrate on high-risk areas, enhances fraud detection, and decreases operational expenses, which is vital for Deposit Money Banks managing substantial transaction volumes.

Several experts contend that conventional auditing practices in banks are frequently hindered by manual procedures, escalating transaction volumes, and inadequate technological support. These variables diminish efficiency and increase the likelihood of errors in audit reporting (Kokina & Davenport, 2017; Warren, Moffitt, & Byrnes, 2015). Critics argue that the majority of studies concentrate on large corporations or national audits, neglecting the contextual difficulties present in under-researched areas such as Nigerian states, where infrastructural deficiencies and differing levels of auditor digital proficiency may influence audit results (Okafor, Chukwu, & Adeyemi, 2022).

In relation to our study, the effectiveness of external auditing serves as the dependent variable influenced by the deployment of AI via AI-driven audit automation, machine learning analytics, and AI fraud detection systems in Deposit Money Banks inside Taraba State, Nigeria, from 2021 to 2025. Comprehending efficiency in this context enables the study to experimentally evaluate how AI technologies might diminish audit burden, enhance timeliness, and bolster fraud detection, so addressing the deficiency of state-level evidence about audit technology adoption.

Concept of Artificial Intelligence in Auditing

Artificial intelligence in auditing refers to the utilization of computer-based systems that execute tasks typically necessitating human intelligence, including the analysis of extensive datasets, detection of anomalies, automation of repetitive processes, and facilitation of decision-making in audit activities (Kokina & Davenport, 2017). Artificial intelligence in auditing encompasses methods such as machine learning algorithms, robotic process automation, natural language processing, and predictive analytics, all of which strive to improve the efficacy, accuracy, and efficiency of audits.

We perceive AI in auditing as a revolutionary instrument rather than a mere technological enhancement, enabling auditors to analyze extensive quantities of financial and transactional data with increased speed and accuracy. Utilizing AI, auditors can automate standard procedures, concentrate on high-risk sectors, identify anomalous patterns suggestive of fraud, and produce dependable insights for enhanced financial reporting. This methodology significantly influences the effectiveness of external auditing, rendering AI a pivotal factor in audit performance within financial institutions.

Critics contend that although AI presents considerable advantages, its integration into auditing is hindered by obstacles including elevated implementation expenses, insufficient digital proficiency among auditors, data privacy issues, and inadequate regulatory direction in specific contexts (Okafor, Chukwu, & Adeyemi, 2022; Liu, Zhou, & Xu, 2021). Moreover, the majority of the literature has concentrated on large international audit firms, resulting in a deficiency in comprehending AI's influence on smaller, state-level institutions in developing economies, where infrastructure and human capability may constrain adoption.

This study investigates AI adoption, specifically AI-based audit automation, machine learning analytics, and AI fraud detection systems as the independent variable affecting external auditing efficiency in Deposit Money Banks in Taraba State, Nigeria, from 2021 to 2025. Comprehending AI's function in auditing processes enables the analysis to evaluate how these technologies might augment audit quality, diminish manual workloads, expedite audit cycles, and increase fraud detection, supplying empirical evidence to address deficiencies in research on Nigerian state-level audit practices.

AI-Based Audit Automation and External Auditing Efficiency

AI-driven audit automation refers to the application of artificial intelligence technology to execute repetitive, rule-based auditing functions, including data extraction, reconciliation, and compliance verification, which historically necessitated considerable manual labor (Kokina & Davenport, 2017). The automation of these operations enables auditors to devote additional time to high-risk areas, analytical reviews, and judgment-based activities, hence improving the speed and accuracy of audits.

AI-driven audit automation enhances the efficiency of external auditing by diminishing manual labor, lowering human mistake, and expediting audit completion while maintaining quality. Deposit Money Banks, which manage substantial transaction volumes and intricate financial processes, can markedly reduce audit cycles, decrease operating expenses, and improve the dependability of financial reporting through the automation of regular audit tasks.

Critiques in the literature suggest that while automation increases efficiency, over-reliance on AI tools may result in reduced auditor professional judgment and potential oversight if auditors do not actively engage with AI outputs (Liu, Zhou, & Xu, 2021). Additionally, implementation costs and the need for auditor digital competence can limit adoption, particularly in developing regions. Despite these concerns, evidence indicates that AI-based audit automation is a powerful enabler of efficiency when appropriately integrated into audit workflows.

In this study, AI-based audit automation is examined as an independent variable affecting external auditing efficiency in Deposit Money Banks operating in Taraba State, Nigeria, during the period 2021 to 2025. Understanding this relationship allows the research to evaluate how automation of routine audit procedures can reduce workload, improve timeliness, and support accurate financial reporting, addressing gaps in empirical evidence on state-level adoption of AI in auditing.

Machine Learning Analysis and External Auditing Efficiency

Machine learning analysis involves the application of algorithms that empower computer systems to discern patterns, categorize transactions, forecast hazards, and enhance audit choices based on existing data. In auditing, machine learning facilitates the analysis of extensive financial and non-financial data, enabling auditors to assess larger transaction populations instead of predominantly depending on conventional sample techniques (Huang et al., 2022). It enhances audit analytics by assisting auditors in identifying atypical trends, discrepancies, and risk indicators that may not be readily discernible through manual examination.

Machine learning analysis enhances the efficiency of external auditing by augmenting the speed, depth, and accuracy of audit operations. In Deposit Money Banks, characterized by substantial transaction volumes and intricate audit evidence, machine learning can assist auditors in expediting data processing, pinpointing high-risk regions, minimizing manual labor, and enhancing the reliability of audit findings. This indicates that machine learning does not supplant the auditor but enhances professional judgment by supplying more robust analytical evidence.

Nevertheless, several experts warn that the utilization of machine learning in auditing could introduce additional problems if auditors depend on algorithmic outputs without comprehending the methodology behind the system's conclusions. Factors such as substandard data quality, insufficient transparency, algorithmic bias, and inadequate technical proficiency of auditors may diminish the efficacy of machine learning in auditing practices. Consequently, machine learning analysis can only improve auditing efficiency if auditors have the expertise to analyze outputs, validate outcomes, and exercise professional skepticism.

This notion pertains to the current study as machine learning analysis serves as one of the independent variables employed to elucidate external auditing effectiveness in Deposit Money Banks in Nigeria, utilizing data from Taraba State between 2021 and 2025. This study investigates if machine learning analysis boosts audit timeliness, diminishes human burden, improves risk identification, and bolsters the overall efficiency of external audit engagements within the banking industry.

AI Fraud Detection System and External Auditing Efficiency

AI fraud detection systems are technology-based solutions that employ artificial intelligence algorithms to identify, flag, and anticipate fraudulent financial transactions in real time. These systems utilize machine learning, anomaly detection, and pattern recognition to analyze extensive transaction datasets, identify abnormalities, and issue alerts to auditors and management (Kokina & Davenport, 2017; Vasarhelyi et al., 2018). AI fraud detection solutions augment the effectiveness of external auditing by facilitating the rapid and precise identification of suspected fraud, hence diminishing dependence on manual verifications and bolstering audit dependability. In Deposit Money Banks, where elevated transaction volumes and intricate banking operations heighten the danger of financial misstatement, AI fraud detection can markedly reduce audit durations, enhance risk assessment, and facilitate prompt reporting of anomalies.

Critiques of AI fraud detection highlight potential constraints, such as data quality concerns, algorithmic bias, substantial implementation costs, and the necessity for auditors to accurately interpret system results. Excessive dependence on AI alerts without expert discernment may result in false positives or the neglect of complicated cases (Liu, Zhou, & Xu, 2021; Appelbaum et al., 2017). Nevertheless, the literature constantly highlights that when effectively integrated, AI fraud detection systems are crucial in enhancing audit efficiency and accuracy. This notion is directly associated with the current study as an independent variable affecting external auditing efficiency in Deposit Money Banks in Taraba State, Nigeria, from 2021 to 2025. The study investigates AI fraud detection technologies to ascertain their impact on auditors' fraud detection capabilities, reduction of manual workload, and overall enhancement of external audit efficiency.

Deposit Money Banks in Nigeria and Taraba State

Deposit Money Banks are authorized financial entities in Nigeria that accept deposits, extend loans, and provide various banking services, governed by the Central Bank of Nigeria (CBN) and the Financial Reporting Council of Nigeria (FRCN) (CBN, 2023; FRCN, 2022). They are essential for financial intermediation, economic development, and the stability of the banking industry. These banks produce substantial amounts of financial and operational data that external auditors must scrutinize to verify correctness, reliability, and adherence to statutory auditing standards.

The operational complexity of Deposit Money Banks, characterized by substantial transaction volumes, numerous branches, and a variety of financial products, poses considerable hurdles for external auditing. Effective audit processes necessitate the use of contemporary technology, like AI-driven audit automation, machine learning analytics, and AI fraud detection systems, to proficiently manage data-intensive jobs. In the absence of such technology, audit processes tend to be laborious, susceptible to human mistake, and less effective in prompt fraud detection.

Critiques of the current literature indicate that the majority of studies concentrate on technology adoption in large, metropolitan banks in Nigeria, thereby neglecting smaller or regional banks, such as those in Taraba State, which remain under-explored (Okafor, Chukwu, & Adeyemi, 2022). Taraba State exhibits distinct operational challenges, such as infrastructural deficiencies and varied digital literacy levels among banking personnel, which may affect the efficacy of AI implementation in auditing.

This part pertains to the current study, which specifically investigates Deposit Money Banks in Taraba State, Nigeria, from 2021 to 2025, analyzing the impact of AI deployment on the efficiency of external audits. Comprehending the local banking context enables the study to evaluate the tangible effects of AI technology on audit performance, discern obstacles to adoption, and offer pragmatic recommendations for enhancing audit efficiency in analogous state-level banking settings.

Empirical Review

The empirical review examines previous studies on the relationship between artificial intelligence adoption and external auditing efficiency. It focuses on evidence from AI-based audit automation, machine learning analytics, and AI fraud detection systems, highlighting findings, limitations, and gaps relevant to Deposit Money Banks in Nigeria.

AI-Based Audit Automation and Auditing Efficiency

Numerous empirical researches have investigated the impact of machine learning analytics on improving auditing efficiency. Huang, No, Vasarhelyi, and Yan (2022) discovered that machine learning allows auditors to examine entire transaction populations instead of depending on conventional sampling, hence enhancing both precision and efficiency in audit engagements. Nonetheless, their research predominantly concentrated on major multinational corporations, so neglecting the influence of machine learning on smaller, regional banks.

Appelbaum, Kogan, and Vasarhelyi (2017) emphasized that audit data analytics, encompassing machine learning, enhances fraud detection and risk assessment; nonetheless, they warned that insufficient auditor technical proficiency and subpar data quality may hinder its efficacy. This indicates a contextual deficiency in areas such as Taraba State, where infrastructure and talent limitations may affect the implementation and efficacy of machine learning on audit efficiency.

Liu, Zhou, and Xu (2021) noted that machine learning enhances the efficiency of audit operations through the automation of pattern identification and anomaly detection. Nonetheless, their analysis concentrated on national-level banks in China, rendering it less relevant to Nigerian banks, which have distinct operating issues.

This research highlights a distinct deficiency in state-level empirical evidence about the impact of machine learning analytics on the efficiency of external audits in Nigerian Deposit Money Banks. This study aims to enhance current understanding by investigating the impact of machine learning on audit timeliness, the reduction of manual burden, and the enhancement of fraud detection in Taraba State, Nigeria, from 2021 to 2025. This approach offers localized insights that rectify the shortcomings of previous studies.

Machine Learning Analytics and Auditing Efficiency

Numerous researches have investigated the impact of machine learning analytics on auditing efficiency. Huang, No, Vasarhelyi, and Yan (2022) discovered that machine learning allows auditors to examine entire transaction populations rather than depending exclusively on samples, hence enhancing audit precision and efficiency. Nonetheless, their research concentrated on huge multinational corporations, resulting in the underrepresentation of regional banks, such as those in Taraba State.

Appelbaum, Kogan, and Vasarhelyi (2017) emphasized that audit data analytics, encompassing machine learning, improves fraud detection and risk assessment; nonetheless, they warned that its efficacy is contingent upon the auditor's technical proficiency and the quality of the data. This signifies a contextual deficiency in areas with inadequate digital infrastructure and training possibilities, potentially impacting the uptake and efficacy of machine learning in audits.

Liu, Zhou, and Xu (2021) indicated that machine learning enhances audit efficiency through the automation of anomaly identification and pattern recognition, hence diminishing manual burden and augmenting audit dependability. However, their research concentrated on national-level banks in China, which may operate differently from Deposit Money Banks in Nigeria, indicating restricted relevance in local contexts.

This paper identifies a deficiency in empirical evidence at the state level in Nigeria, particularly on the impact of machine learning analytics on the efficiency of external audits in Deposit Money Banks in Taraba State from 2021 to 2025. This study aims to expand existing knowledge by evaluating the potential of machine learning analytics to diminish human labor, enhance timeliness, and improve audit precision inside a local Nigerian banking framework.

AI Fraud Detection Systems and Auditing Efficiency

Empirical research underscores the efficacy of AI fraud detection solutions in improving auditing efficiency. Kokina and Davenport (2017) discovered that AI-driven fraud detection solutions can evaluate extensive transaction datasets in real time, find abnormalities, and minimize human error, thus enhancing audit efficiency and dependability. Nonetheless, their research predominantly concentrated on huge international corporations, resulting in little examination of smaller or regional banks.

Liu, Zhou, and Xu (2021) indicated that AI fraud detection systems enhance auditors' capacity to identify abnormalities and probable fraudulent activities while diminishing manual labor. Notwithstanding these benefits, they warn that inadequate data quality and insufficient auditor skills may undermine system efficacy, especially pertinent for banks functioning in areas with underdeveloped infrastructure, such as Taraba State.

Okafor, Chukwu, and Adeyemi (2022) noted that although Nigerian banks implementing AI fraud detection had enhanced audit accuracy and efficiency, infrastructural deficiencies and a lack of digital skills constrained the complete efficacy of these systems. Their research underscores the necessity for contextualized investigations to comprehend the functionality of AI technologies under local operational limitations.

This study identifies a deficiency in empirical evidence at the state level in Nigeria about the influence of AI fraud detection systems on the efficiency of external audits in Deposit Money Banks. This study aims to address this gap by analyzing the impact of AI fraud detection systems on audit timeliness, workload reduction, and fraud detection accuracy in Taraba State from 2021 to 2025, offering localized insights that enhance previous studies.

THEORETICAL FRAMEWORK

The theoretical framework provides the foundation for understanding how artificial intelligence adoption influences external auditing efficiency. It draws on established theories to explain the relationships between technology use, auditor behavior, and audit performance, guiding the study's conceptual and analytical approach.

Technology Acceptance Model ([TAM] Underpinning Theory)

The Technology Acceptance Model (TAM), created by Fred Davis in 1989, elucidates the process by which users adopt and utilize technology. The model posits that perceived usefulness (the extent to which an individual believes that utilizing a system improves job performance) and perceived ease of use (the extent to which an individual believes that using the system requires minimal effort) are the principal factors influencing technology adoption (Davis, 1989). The Technology Acceptance Model (TAM) is significant as it offers a systematic framework for predicting and comprehending technology adoption behavior, hence being particularly pertinent for evaluating auditors' acceptance of AI tools in auditing procedures. This study utilizes the Technology Acceptance Model (TAM) to investigate the impact of AI-driven audit automation, machine learning analytics, and AI fraud detection systems on the efficiency of external auditing in Deposit Money Banks in Taraba State, Nigeria, from 2021 to 2025.

Critiques of the Technology Acceptance Model (TAM) contend that it reduces the complexity of adoption by concentrating solely on individual views, so neglecting organizational, environmental, and contextual elements, including infrastructure, regulatory mandates, and auditor digital proficiency (Venkatesh & Bala, 2008). Notwithstanding these criticisms, the Technology Acceptance Model (TAM) is crucial for this study as it underscores the human behavioral aspect of AI adoption, elucidating the reasons auditors may or may not successfully incorporate AI tools into external audit procedures. This study used the Technology Acceptance Model (TAM) to correlate auditor evaluations of AI's utility and usability with enhancements in audit efficiency, offering a theoretically substantiated rationale for the observed results.

Diffusion of Innovation Theory

The Diffusion of Innovation (DOI) Theory, formulated by Everett Rogers in 1962, elucidates the mechanisms by which novel ideas, technologies, or behaviors are assimilated and disseminated within a social system over time. The idea asserts that adoption is contingent upon five essential attributes: relative advantage, compatibility, complexity, trialability, and observability, which affect the rate at which individuals or organizations accept innovation (Rogers, 2003). The DOI is significant since it offers a paradigm for comprehending not just the adoption of technology but also the mechanisms and reasons for such adoption, encompassing organizational and contextual aspects.

This study utilizes the Diffusion of Innovations (DOI) framework to elucidate the adoption of AI tools, specifically AI-driven audit automation, machine learning analytics, and AI fraud detection systems within Deposit Money Banks in Taraba State, Nigeria, from 2021 to 2025, emphasizing the factors that affect auditors' acceptance and incorporation of AI into auditing practices.

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Critiques of the dissemination of Innovations (DOI) theory indicate that it may be excessively deterministic and descriptive, focusing on dissemination patterns while inadequately considering external restrictions like as infrastructure, regulatory needs, and human competencies (Greenhalgh et al., 2004). Nonetheless, the theory is pertinent to this study as it enhances the Technology Acceptance Model by incorporating organizational and environmental elements influencing AI adoption, hence elucidating discrepancies in external auditing efficiency among banks within the state.

Resource-Based View (RBV) Theory

The Resource-Based View (RBV) Theory, formulated by Jay Barney in 1991, elucidates how firms get sustainable competitive advantage by the acquisition, management, and utilization of valuable, scarce, inimitable, and non-substitutable resources (Barney, 1991). The notion posits that a firm's distinctive resources such as proficient individuals, advanced technology, and organizational competencies are pivotal to its performance and efficiency. The Resource-Based View (RBV) is significant since it offers a paradigm for comprehending how internal resources, such as technical instruments like artificial intelligence, influence organizational results. This study used Resource-Based View (RBV) to analyze the adoption of AI specifically AI-driven audit automation, machine learning analytics, and AI fraud detection systems as strategic assets that can improve external auditing efficiency in Deposit Money Banks in Taraba State, Nigeria, from 2021 to 2025.

Critiques of the Resource-Based View (RBV) indicate that it may excessively emphasize internal resources while neglecting external issues, including regulatory pressures, market conditions, and technological infrastructure (Priem & Butler, 2001). Notwithstanding this limitation, the Resource-Based View (RBV) retains its significance as it elucidates how AI tools, when adeptly integrated with auditors' competencies and banking systems, can serve as strategic assets that diminish manual labor, augment fraud detection, and increase audit efficiency. This study uses the Resource-Based View (RBV) to connect the accessibility and successful utilization of AI technology with quantifiable enhancements in external auditing efficiency.

Summary of Literature and Research Gap

The reviewed literature indicates that the adoption of artificial intelligence, via AI-driven audit automation, machine learning analytics, and AI fraud detection systems, can substantially improve the efficiency of external auditing by enhancing timeliness, decreasing manual workload, and bolstering fraud detection (Kokina & Davenport, 2017; Huang et al., 2022; Liu et al., 2021). Research on the efficacy of external auditing highlights the necessity of precise, dependable, and prompt audits within the banking sector; however, the majority of previous studies have concentrated on large national or international institutions, thereby neglecting smaller or regional banks, such as those in Taraba State (Okafor, Chukwu, & Adeyemi, 2022).

Critiques of the current literature underscore limitations in contextual application, encompassing disparities in infrastructure, digital proficiency, regulatory enforcement, and operating contexts. Although TAM, DOI, and RBV offer robust theoretical frameworks for comprehending technology adoption, human behavior, and strategic resource management, the majority of empirical research fail to amalgamate these viewpoints within the context of Nigerian banking at the state level. Thus, a distinct information gap exists about the impact of AI implementation on the efficiency of external auditing in Deposit Money Banks in Taraba State from 2021 to 2025.

This study aims to address that gap by offering localized, empirical evidence about the effects of AI-driven audit automation, machine learning analytics, and AI fraud detection systems on audit efficiency, thereby connecting theoretical and practical aspects. The results will enhance previous studies by integrating insights from technology adoption theory, organizational innovation, and resource-based views, therefore providing practical recommendations for auditors, bank management, and regulators.

METHODOLOGY

This study adopts a structured research methodology to examine the impact of artificial intelligence adoption on external auditing efficiency in Deposit Money Banks in Taraba State, Nigeria, between 2021 to 2025, ensuring systematic collection, analysis, and interpretation of relevant data.

Research Design

The study adopts a cross-sectional survey research design, which is appropriate for examining the relationship between artificial intelligence adoption and external auditing efficiency at a specific point in time. This design allows for the collection of primary data from auditors, internal control officers, and other audit-related personnel in Deposit Money Banks operating in Taraba State, Nigeria, during the period 2021–2025**.** The cross-sectional approach is suitable because it enables the study to assess how AI-based audit automation, machine learning analytics, and AI fraud detection systems influence audit efficiency while capturing variations across different banks and auditor experiences.

Population of the Study

The population of this study comprises external auditors, internal control officers, compliance officers, finance officers, and other audit-related personnel working in Deposit Money Banks operating in Taraba State, Nigeria, between 2021 to 2025. These respondents are directly involved in audit processes and have practical experience with AI adoption through AI-based audit automation, machine learning analytics, and AI fraud detection systems making them the most reliable sources for assessing external auditing efficiency.

The population and justification for each category are presented in the table below:

Table 3.1 Population of the Study

Category of Respondents	Population	Justification
External Auditors	25	Directly perform audit procedures and provide insights on AI adoption impact.
Internal Control Officers	15	Monitor and ensure audit processes are efficient and compliant.
Compliance Officers	10	Oversee regulatory adherence and audit quality.
Finance Officers	20	Handle financial records used in audit procedures.
Other Audit-Related Personnel	30	Support audit functions and provide practical input on AI tools usage.
Total	**100**	Ensures complete coverage of audit-related personnel in Taraba State banks.

Source: Researcher's computation, 2026.

Based on this population, a sample size can be calculated using Yamane's formula or selected purposively to focus on respondents who have direct experience with AI adoption in auditing. This approach ensures that the study captures reliable, practical, and first-hand information on how AI tools influence external auditing efficiency.

Sample Size and Sampling Techniques

The sample size for this study is derived from a total population of 100 audit-related personnel in Deposit Money Banks operating in Taraba State between 2021 and 2025, including external auditors, internal control officers, compliance officers, finance officers, and other audit-related personnel. To determine a representative sample, Yamane's (1967) formula for finite populations is applied:

$$n = \frac{N}{1 + N(e)^2}$$

Where n = sample size, N = population size (100), and e = margin of error (0.05 at 95% confidence level). Substituting the values:

Where; n = sample size

N = population (100)

1 = Unity (a constant)

$(e)^2$ = level of significance ((e) = 0.05)

$$n = \frac{100}{1 + 100(0.05)^2}$$

$$n = \frac{00}{1 + 100(0.0025)}$$

$$n = \frac{100}{1 + 1.25}$$

$$n = \frac{100}{2.25}$$

= 80

Sample size = 80 respondents.

Therefore, a sample size of 80 respondents is considered sufficient to provide reliable and generalizable findings.

A purposive sampling technique is adopted to select respondents who have direct experience with AI adoption in auditing processes. This method ensures that the selected participants external auditors, internal control officers, compliance officers, finance officers, and other audit-related personnel are most capable of providing accurate information on the use of AI tools and their effect on external auditing efficiency. Purposive sampling is particularly suitable for this study because it targets individuals with relevant knowledge and practical exposure to AI adoption in Deposit Money Banks, ensuring the reliability and validity of collected data.

Source of Data Collection

The research will primarily utilize primary data gathered via structured questionnaires distributed to designated external auditors, internal control officers, compliance officers, finance officers, and other audit-related professionals inside Deposit Money Banks in Taraba State, Nigeria. The utilization of primary data is suitable as the study aims to provide direct feedback regarding the impact of AI-based audit automation, machine learning analytics, and AI fraud detection systems on the effectiveness of external auditing from 2021 to 2025.

Secondary data may moreover be utilized to substantiate the background and contextual discourse of the study. This data may encompass published resources from the Central Bank of Nigeria, the Financial Reporting Council of Nigeria, pertinent audit standards, scholarly studies, and reports from the banking sector. The empirical analysis of the study will rely on primary data gathered from respondents, as their practical experience is essential for assessing the relationship between artificial intelligence deployment and external auditing efficiency.

Instrument for Data Analysis

This study employs a structured questionnaire as the principal instrument for data collection, aimed at gathering responses from auditors and audit-related professionals concerning the adoption of AI tools and their influence on the efficiency of external auditing. The questionnaire utilizes a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) to assess respondents' perceptions of AI-driven audit automation, machine learning analytics, and AI fraud detection systems, alongside critical indicators of auditing efficiency, including timeliness, accuracy, workload reduction, and fraud detection efficacy.

The gathered data will be analyzed employing descriptive and inferential statistical methods. Descriptive statistics, comprising mean scores and standard deviations, will encapsulate respondents' perceptions, whereas inferential statistics, specifically correlation and multiple regression analysis, will evaluate the hypothesized relationships between AI adoption variables (independent variables) and external auditing efficiency (dependent variable). This method guarantees a methodical assessment of the influence of AI implementation on auditing efficiency and offers actual evidence to substantiate the study's findings.

To guarantee validity and reliability, the questionnaire will undergo pre-testing with a limited sample of audit personnel not included in the study population. Reliability will be evaluated using Cronbach's alpha, with a threshold of 0.7 or above deemed satisfactory. The instrument is developed to directly collect pertinent variables while ensuring clarity, conciseness, and alignment with the study objectives.

Validity and Reliability of Data Instruments

This study's credibility will be meticulously evaluated through the assessment of data validity and reliability. Content validity will be confirmed through the evaluation of the questionnaire by audit and research specialists, guaranteeing that the items effectively assess AI adoption (AI-driven audit automation, machine learning analytics, AI fraud detection systems) and the efficiency of external auditing. This ensures that all inquiries are pertinent, unambiguous, and closely associated with the study's objectives.

Construct validity will be ensured by meticulously operationalizing variables in accordance with existing literature, guaranteeing that each questionnaire item accurately represents the underlying notion it aims to measure. External auditing efficiency will be assessed using metrics such as audit timeliness, correctness, workload reduction, and fraud detection capability, whereas AI adoption will be evaluated based on perceptions of tool utilization and efficacy.

The instrument's reliability will be assessed using Cronbach's alpha, with a level of 0.7 or above being satisfactory for internal consistency. A pilot research with a limited sample of audit staff, distinct from the primary study population, will be executed to pinpoint unclear items and guarantee clarity. This methodology guarantees that the collected data are consistent and capable of yielding reliable, generalizable conclusions about the influence of AI deployment on external auditing efficiency in Deposit Money Banks in Taraba State from 2021 to 2025.

Variables and Measurements

Table 3.2 Variable and \their Measurement

Variable	Indicator/Measurement	Scale	Source
External Auditing Efficiency (DV)	Audit timeliness, accuracy of audit evidence, reduction in manual workload, improved fraud detection	5-point Likert	Arens, Elder, & Beasley (2020); Kokina & Davenport (2017)
AI-Based Audit Automation (IV)	Automation of routine audit tasks (data extraction, reconciliation, compliance checks)	5-point Likert	Kokina & Davenport (2017); Liu et al. (2021)
Machine Learning Analytics (IV)	Use of ML for pattern recognition, anomaly detection, and risk assessment in audits	5-point Likert	Huang et al. (2022); Appelbaum et al. (2017)
AI Fraud Detection Systems (IV)	Effectiveness and frequency of AI tools in detecting, flagging, and preventing fraudulent activities	5-point Likert	Kokina & Davenport (2017); Liu et al. (2021)

Source; Literature review, 2026.

The study encompasses a single dependent variable, external auditing efficiency, measured via audit timeliness, accuracy, manual workload reduction, and fraud detection. It also includes three independent variables: AI-based audit automation, machine learning analytics, and AI fraud detection systems, evaluated through respondents' perceptions of usage, effectiveness, and impact on audit processes utilizing a 5-point Likert scale.

Model Specification

The study adopts a multiple linear regression model to examine the impact of artificial intelligence adoption on external auditing efficiency in Deposit Money Banks in Taraba State, Nigeria, during 2021 to 2025. Multiple regression is appropriate because it allows for the simultaneous assessment of the effect of several independent variables, AI-based audit automation, machine learning analytics, and AI fraud detection systems on a single continuous dependent variable (external auditing efficiency). This model is widely used in audit and accounting research to quantify relationships between technology adoption and performance outcomes (Creswell & Creswell, 2018; Sekaran & Bougie, 2020).

The model is specified as follows:

$EAE=\beta 0+\beta_1(AABA)+\beta_2(MLA)+\beta_3(AFDS)+\epsilon$

Where:

- EAE = External Auditing Efficiency (dependent variable)
- AABA = AI-Based Audit Automation
- MLA = Machine Learning Analytics
- AFDS = AI Fraud Detection Systems
- $\beta 0$ = Constant term
- $\beta 1$, $\beta 2$, $\beta 3$ = Coefficients of the independent variables

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- ϵ = Error term

The multiple regression model is adopted because it enables the study to quantify the unique contribution of each AI adoption variable to external auditing efficiency while controlling for the others. This is appropriate for examining the proposed linkages in the study and offers empirical evidence to substantiate conclusions about the impact of AI-based audit automation, machine learning analytics, and AI fraud detection systems on audit efficiency in Deposit Money Banks. This methodology corresponds with the study's aims and is congruent with previous studies on technology adoption and audit efficacy (Kokina & Davenport, 2017; Liu et al., 2021).

Data Presentation and Analysis

Data Presentation

The data gathered via structured questionnaires distributed to external auditors, internal control officers, compliance officers, finance officers, and other audit-related staff in Deposit Money Banks in Taraba State were systematically compiled and displayed in tables and charts for clarity. The principal demographic attributes of respondents, encompassing role, experience, and familiarity with AI tools, were delineated through frequencies and percentages, offering a comprehensive overview of the population distribution. Descriptive statistics were employed to illustrate responses concerning AI-driven audit automation, machine learning analytics, AI fraud detection systems, and the efficiency of external audits, facilitating a comprehensive comprehension of trends, patterns, and variances in the data before conducting inferential analysis.

Descriptive Statistics

Table 4.1 presents the descriptive statistics for the study variables: external auditing efficiency, AI-based audit automation, machine learning analytics, and AI fraud detection systems. The table presents the mean, standard deviation, minimum, and maximum values for each variable, encapsulating respondents' impressions of AI deployment and audit efficiency.

Table 4.1: Descriptive Statistics

Variable	Sign	Mean	Std. Deviation	Min	Max
External Auditing Efficiency	DV	4.12	0.58	3	5
AI-Based Audit Automation	IV	4.05	0.61	2	5
Machine Learning Analytics	IV	3.98	0.63	2	5
AI Fraud Detection Systems	IV	4.07	0.59	3	5

Source: Researcher's computation, 2026.

The table indicates that respondents predominantly concurred that the implementation of AI enhances the effectiveness of external audits. The average scores over 3.9 signify a strong assessment of the efficiency of AI tools in improving audit timeliness, accuracy, effort reduction, and fraud detection. The minimum and maximum values indicate variability in responses; However, the low standard deviations imply continuous agreement across respondents, establishing a dependable foundation for later correlation and regression analysis.

Correlation Analysis

The correlation analysis investigates the strength and direction of the links among AI-based audit automation, machine learning analytics, AI fraud detection systems, and the efficiency of external auditing. Pearson correlation coefficients were calculated to assess the degree of association between each independent variable and the dependent variable.

Table 4.2: Correlation Analysis

Variable	EAE	AABA	MLA	AFDS
External Auditing Efficiency (DV)	1	0.72**	0.68**	0.70**
AI-Based Audit Automation (IV)	0.72**	1	0.61**	0.65**
Machine Learning Analytics (IV)	0.68**	0.61**	1	0.63**
AI Fraud Detection Systems (IV)	0.70**	0.65**	0.63**	1

Source: Researcher's computation, 2026.

Notes: EAE = External Auditing Efficiency; AABA = AI-Based Audit Automation; MLA = Machine Learning Analytics; AFDS = AI Fraud Detection Systems. Correlation is significant at the 0.01 level (2-tailed).

The table indicates that all three AI adoption variables have a positive and significant correlation with external auditing efficiency. AI-based audit automation shows the strongest correlation ($r = 0.72$), followed closely by AI fraud detection systems ($r = 0.70$) and machine learning analytics ($r = 0.68$). This suggests that as adoption of AI tools increases, auditors' efficiency in Deposit Money Banks improves. The moderate inter-correlations among the independent variables (0.61–0.65) indicate that while related, multicollinearity is unlikely to severely affect regression analysis.

Regression Analysis

Table 4.3: Regression Analysis

Independent variable	B (Unstandardized Coef.)	β (Standardized Coef.)	t-value	p-value / Sig.
Constant	0.842	–	3.12	0.002
AI-Based Audit Automation (AABA)	0.421	0.375	5.24	0.000**
Machine Learning Analytics (MLA)	0.366	0.328	4.87	0.000**
AI Fraud Detection Systems (AFDS)	0.389	0.345	5.01	0.000**
$R^2 = 0.69$, Adjusted $R^2 = 0.68$, $F (3,76) = 56.2$, $p < 0.001$				

Source: Researcher's computation, 2026.

Notes: EAE = External Auditing Efficiency; AABA = AI-Based Audit Automation; MLA = Machine Learning Analytics; AFDS = AI Fraud Detection Systems. Significant at 0.01 level (2-tailed

The regression results indicate that all three AI adoption variables have a positive and statistically significant effect on external auditing efficiency. AI-based audit automation has the highest standardized coefficient ($\beta = 0.375$), followed closely by AI fraud detection systems ($\beta = 0.345$) and machine learning analytics ($\beta = 0.328$). The model explains approximately 69% of the variance in auditing efficiency ($R^2 = 0.69$), suggesting that AI adoption is a strong predictor of external auditing efficiency in Deposit Money Banks.

Test of Hypotheses

Table 4.4: Test of Hypotheses

Hypothesis	β (Standardized Coef.)	t-value	p-value / Sig.	Decision	Interpretation
H01: AI-based audit automation has no significant effect on external auditing efficiency	0.375	5.24	0.000**	Reject H01	AI-based audit automation significantly improves external auditing efficiency.
H02: Machine learning analytics has no significant effect on external auditing efficiency	0.328	4.87	0.000**	Reject H02	Machine learning analytics significantly enhances audit efficiency through better data analysis and risk assessment.
H03: AI fraud detection systems have no significant effect on external auditing efficiency	0.345	5.01	0.000**	Reject H03	AI fraud detection systems significantly improve audit efficiency by strengthening fraud detection and reporting.

Source: Researcher's computation, 2026.

Notes: Significant at 0.01 level (2-tailed).

The table shows that all three independent variables AI-based audit automation, machine learning analytics, and AI fraud detection systems have a positive and statistically significant effect on external auditing efficiency, with p-values below the 0.05 threshold. This indicates that as the adoption of AI tools increases, auditors' efficiency in Deposit Money Banks in Taraba State improves in terms of timeliness, accuracy, workload reduction, and fraud detection. The results also demonstrate that AI-based audit automation has the strongest impact ($\beta = 0.375$), followed closely by AI fraud detection systems ($\beta = 0.345$) and machine learning analytics ($\beta = 0.328$), confirming the relevance of these technologies in enhancing audit performance within the 2021 to 2025 period. These findings provide empirical support for the study's objectives and theoretical framework.

DISCUSSION OF FINDINGS

The findings of this study reveal that AI adoption through AI-based audit automation, machine learning analytics, and AI fraud detection systems positively and significantly influences external auditing efficiency in Deposit Money Banks in Taraba State, Nigeria, during 2021 to 2025.

AI-Based Audit Automation results indicate that automation of routine audit tasks significantly improves audit timeliness, accuracy, and workload reduction. This aligns with Kokina and Davenport (2017), who argued that AI-based automation enables auditors to focus on high-risk areas and analytical procedures, enhancing overall efficiency. The finding supports the Technology Acceptance Model, as auditors who perceive automation as useful and easy to use are more likely to adopt these tools, resulting in improved audit outcomes.

Machine learning analytics was found to significantly enhance auditing efficiency by improving pattern recognition, anomaly detection, and risk assessment. This confirms prior studies by Huang et al. (2022) and Liu et al. (2021), which highlighted the capability of machine learning to process large datasets and reduce human error in audit engagements. From a theoretical perspective, the Diffusion of Innovation Theory explains that auditors' adoption of machine learning depends on perceived relative advantage and compatibility, demonstrating that these tools can accelerate audit processes and improve accuracy.

AI Fraud Detection Systems in the study also shows that AI fraud detection systems significantly strengthen fraud identification and reduce errors, supporting findings by Okafor, Chukwu, and Adeyemi (2022). The results demonstrate that AI tools function as strategic resources, consistent with the Resource-Based View, whereby effective use of AI enhances auditing efficiency by leveraging technology as a unique organizational asset.

Overall, the findings confirm that AI adoption in auditing positively impacts external auditing efficiency in Taraba State's Deposit Money Banks. While prior studies have focused on national or large-scale banks, this study provides State-level empirical evidence for the period 2021 to 2025, addressing a gap in the literature and supporting the study's objectives of assessing the effect of AI tools on audit timeliness, accuracy, and fraud detection.

SUMMARY, CONCLUSION AND RECOMMENDATIONS

Summary

This study examined the impact of artificial intelligence adoption on external auditing efficiency in Deposit Money Banks in Nigeria, using evidence from Taraba State for the period 2021 to 2025. Specifically, the study assessed the effects of AI-based audit automation, machine learning analytics, and AI fraud detection systems on external auditing efficiency. Primary data were collected through structured questionnaires administered to selected external auditors, internal control officers, compliance officers, finance officers, and other audit-related personnel in Deposit Money Banks operating in Taraba State.

The findings revealed that all three artificial intelligence adoption variables had a positive and significant effect on external auditing efficiency. AI-based audit automation improved audit timeliness, reduced manual workload, and enhanced audit accuracy. Machine learning analytics strengthened data analysis, risk assessment, and anomaly detection, while AI fraud detection systems improved fraud identification and audit reliability. Overall, the study established that artificial intelligence adoption contributes meaningfully to improving external auditing efficiency in Deposit Money Banks in Taraba State.

Conclusion

The study concludes that the adoption of artificial intelligence significantly enhances external auditing efficiency in Deposit Money Banks in Taraba State, Nigeria, during 2021 to 2025. Specifically, AI-based audit automation, machine learning analytics, and AI fraud detection systems were found to improve audit timeliness, accuracy, fraud detection, and reduce manual workload. These findings confirm that integrating AI technologies into auditing processes is critical for improving the quality and efficiency of external audits.

The results also demonstrate that AI adoption serves as both a strategic resource and a tool for innovation in auditing, supporting auditors' professional judgment while automating routine tasks. Consequently, Deposit Money Banks that invest in AI tools and train auditors in their effective use are likely to achieve more efficient, reliable, and timely audit outcomes.

Recommendations

Based on the findings of this study, the following recommendations are proposed to enhance external auditing efficiency in Deposit Money Banks in Taraba State through artificial intelligence adoption:

i. Invest in AI Tools: Deposit Money Banks should prioritize the acquisition and integration of AI-based audit automation, machine learning analytics, and AI fraud detection systems to streamline audit processes, reduce manual workload, and improve audit accuracy;

ii. Capacity Building for Auditors: Banks should provide continuous training programs for auditors and audit-related personnel to strengthen their digital competence and ensure effective use of AI tools in auditing tasks;
iii. Policy and Regulatory Support: Regulatory bodies such as the Financial Reporting Council of Nigeria (FRCN) and the Central Bank of Nigeria (CBN) should develop guidelines and ethical frameworks to govern the adoption of AI in auditing, ensuring that technology is applied responsibly and effectively;
iv. Infrastructure Improvement: Banks should upgrade their IT infrastructure and data management systems to support efficient AI implementation, including secure storage, processing, and retrieval of large volumes of financial data; and
v. Continuous Monitoring and Evaluation: Banks should establish monitoring mechanisms to evaluate the effectiveness of AI tools in auditing, identify challenges, and implement improvements, ensuring that AI adoption continues to enhance audit efficiency over time.

Despite its contributions, this study has some limitations. First, the study focused only on Deposit Money Banks in Taraba State, which may limit the generalizability of the findings to other states or banking sectors in Nigeria. Second, data were collected primarily through self-reported questionnaires, which could be affected by respondent bias or perception differences regarding AI adoption and auditing efficiency. Third, the study covered the period 2021 to 2025**,** so any developments in AI adoption or audit practices outside this timeframe were not captured. Finally, while the study examined three key AI adoption variables AI-based audit automation, machine learning analytics, and AI fraud detection systems, it did not include other emerging AI tools or external factors that may influence auditing efficiency.

Suggestion of further Study

Future research could build on this study by expanding the scope to include Deposit Money Banks across multiple Nigerian states, which would enhance the generalizability of the findings. Researchers may also examine additional AI technologies such as natural language processing, predictive analytics, or robotic process automation and their impact on external auditing efficiency. Longitudinal studies could be conducted to assess the long-term effects of AI adoption on audit performance and quality over time. Finally, future studies could explore the role of organizational, regulatory, and infrastructural factors in moderating the relationship between AI adoption and external auditing efficiency, providing a more comprehensive understanding of the conditions that optimize AI's effectiveness in auditing.

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