THE IMPACT OF ARTIFICIAL INTELLIGENCE ON AUDIT QUALITY AND EFFICIENCY

BY

OFILI DAVID EBUKA
MGS2104613

DEPARTMENT OF ACCOUNTING
FACULTY OF MANAGEMENT SCIENCES
UNIVERSITY OF BENIN
BENIN CITY

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A RESEARCH PROJECT SUBMITTED TO THE DEPARTMENT OF ACCOUNTING, FACULTY OF MANAGEMENT SCIENCES, UNIVERSITY OF BENIN, IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF SCIENCE (B.Sc) DEGREE IN ACCOUNTING.

OCTOBER, 2025

DECLARATION

I hereby declare that:

i. This study is based on a study undertaken by me in the Department of Accounting, Faculty of Management Sciences, University of Benin, Benin City, under the supervision of **Dr. HENRY EMIFE MONYE-EMINA**

ii. This work has not been previously submitted for the award of degree elsewhere.

iii. Ideas and views are product of my personal research and where the view of others have been expressed, they have been duly acknowledged.

iv. Any liability arising from this work is to be wholly borne by me alone.

_____ _____

OFILI DAVID EBUKA **DATE**

CERTIFICATION

We, the undersigned hereby certify that this research project was carried out by **OFILI DAVID EBUKA** with matriculation number MGS2104613 of the Department of Accounting, Faculty of Management Sciences, University of Benin, Benin city and do approve that it is adequate in scope and quality in partial fulfilment for the award of Bachelor of Science (B.Sc.) degree in Accounting.

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Dr. HENRY EMIFE MONYE-EMINA **Date**
(Project Supervisor)

_____ _____

Dr. IKHU-OMOREGBE GODSTIME **Date**
(Project Coordinator)

_____ _____

Prof. OSASU OBARETIN **Date**
(Head of Department)

DEDICATION

This project is dedicated to God Almighty for His grace, guidance, and strength throughout this journey.

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ABSTRACT

This study explores the extent to which AI-driven tools such as machine learning, natural language processing, and data analytics enhance auditors' ability to detect anomalies, assess risks, and provide deeper insights into financial statements. AI's capacity to process vast datasets in real time reduces human error, strengthens fraud detection, and enables auditors to focus on judgment-intensive tasks, thereby improving audit quality. Moreover, automation of repetitive audit procedures accelerates workflow, minimizes costs, and enhances overall efficiency. However, the adoption of AI also raises concerns about data security, auditor independence, ethical implications, and the need for continuous skill development. This paper argues that while AI does not replace professional skepticism and human judgment, it serves as a powerful enabler that reshapes auditing practices toward greater reliability, transparency, and efficiency. The findings contribute to ongoing debates on the future of auditing and provide practical insights for regulators, practitioners, and stakeholders.

CHAPTER ONE

1.0 Background of the Study

Auditing remains one of the most important mechanisms for ensuring the credibility, reliability, and transparency of financial reporting. In both private and public organizations, audits serve as a safeguard to stakeholders by providing assurance that financial statements present a true and fair view of an entity's financial position (Windy, et al.,2025) Traditionally, auditing has been heavily reliant on manual processes, sampling techniques, and the professional judgment of auditors. However, in today's business environment, where financial transactions are increasingly complex, voluminous, and digitalized, the limitations of traditional auditing methods have become more evident. These limitations have raised concerns about audit quality and efficiency, particularly in detecting fraud, assessing risk, and ensuring timely reporting. Consequently, technological advancements, particularly in Artificial Intelligence (AI), are being integrated into auditing practice as a transformative tool (Mulyadi, et al.,2025).

Artificial Intelligence refers to computer systems that are capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and decision-making. In the auditing context, AI applications include natural language processing (NLP) for analysing unstructured financial data, machine learning algorithms for detecting anomalies in financial transactions, and robotic process automation (RPA) for handling repetitive audit procedures. These tools enable auditors to move beyond

traditional sampling methods to examine entire populations of data, thereby increasing the scope, accuracy, and reliability of audit work. For example, AI-powered software can analyse thousands of financial transactions within seconds, detect irregular patterns, and flag potential fraud risks that human auditors might overlook. As organizations increasingly adopt AI-driven systems in their operations, auditors too must embrace AI tools to remain relevant and effective (Pérez-Calderón, et. al.,2025).

Globally, regulators, audit firms, and professional bodies have begun to emphasize the potential of AI to improve audit quality. The International Federation of Accountants (IFAC) and the Big Four audit firms (KPMG, Deloitte, PwC, and EY) have consistently highlighted the role of emerging technologies in enhancing audit practice. Deloitte (2022), for instance, reported that AI-based audit solutions have significantly reduced errors in risk assessment and improved efficiency in data processing. Similarly, PwC has developed AI platforms such as "GL.ai," which uses machine learning to identify unusual accounting entries and potential fraud risks. These developments illustrate how AI is gradually reshaping the auditing profession, creating new opportunities but also presenting challenges related to auditor independence, ethical considerations, data security, and skills adaptation (Baharom, 2025).

In Nigeria and other emerging economies, the adoption of AI in auditing remains at a developing stage. While large multinational corporations and international audit firms have made significant investments in AI tools, many indigenous audit firms and

practitioners continue to rely heavily on manual processes. This raises questions about the competitiveness of local auditors in an increasingly digital business environment. Moreover, regulators such as the Financial Reporting Council of Nigeria (FRCN) and the Institute of Chartered Accountants of Nigeria (ICAN) are gradually recognizing the need for technological adaptation but have yet to issue comprehensive guidelines on AI integration in auditing. The disparity in adoption between developed and developing economies underscores the importance of empirical studies that assess the practical impact of AI on audit quality and efficiency within different contexts.

Audit quality has been defined as the probability that an auditor will both detect and report material misstatements in financial statements. Efficiency, on the other hand, relates to the ability of auditors to achieve audit objectives using minimal resources, time, and cost. In recent years, the credibility of audits has been questioned due to high-profile corporate scandals such as the Wirecard case in Germany (2020) and the collapse of Steinhoff International (2017), where auditors failed to detect significant financial irregularities. These scandals have highlighted gaps in traditional audit methodologies and the urgent need for more advanced, technology-driven approaches. AI has the potential to address these gaps by providing auditors with deeper insights, predictive analytics, and real-time monitoring capabilities, thereby enhancing both quality and efficiency (Baharom, 2025).

Despite these potentials, the integration of AI into auditing practice is not without challenges. Concerns have been raised about the interpretability of AI models (often referred to as the "black box problem"), auditor dependence on technology, and the potential erosion of professional judgment. Ethical issues also arise regarding data privacy, cybersecurity, and the risk of bias in AI algorithms. Furthermore, auditors require new skills to operate AI tools effectively, which raises questions about the adequacy of existing training and professional development frameworks (Baharom, 2025). Therefore, while AI promises significant improvements in audit practice, its implementation must be carefully evaluated to balance technological efficiency with professional skepticism and ethical responsibility.

Given this background, this study seeks to examine the impact of Artificial Intelligence on audit quality and efficiency, with a focus on identifying the extent to which AI enhances audit effectiveness, the challenges associated with its adoption, and the implications for auditors, regulators, and organizations. By exploring these dimensions, the research will contribute to the ongoing discourse on the future of auditing and provide empirical evidence to guide policy, practice, and further research. Ultimately, the study recognizes that the future of auditing lies at the intersection of technology and human expertise, and understanding this relationship is critical for safeguarding the integrity of financial reporting in the digital age.

1.2 Statement of the Problem

The credibility of financial reporting is essential for maintaining investor confidence, promoting economic growth, and ensuring good corporate governance. Auditing plays a central role in safeguarding this credibility by providing an independent and objective assessment of the accuracy of financial statements. However, the traditional audit approach, which largely relies on manual processes, sample testing, and the professional judgment of auditors, has been increasingly criticized for its limitations in handling the growing complexity and volume of financial data in modern organizations. In today's fast-paced, technology-driven business environment, traditional audit methods often fall short in detecting material misstatements, identifying fraudulent activities, and delivering timely results. This has raised serious questions about the efficiency and quality of audits conducted using conventional approaches.

High-profile corporate scandals in recent decades have further exposed the weaknesses of traditional auditing. Cases such as Enron, Lehman Brothers, Wirecard, and Steinhoff International demonstrated how auditors failed to detect significant fraud and misreporting despite conducting statutory audits. These failures have damaged public trust in the audit profession and have led regulators, investors, and other stakeholders to demand higher audit quality, better risk detection, and more efficient audit processes. In

Nigeria, similar concerns have been raised following the collapse of firms and financial institutions where auditors were accused of negligence or complicity in failing to detect financial irregularities. Such controversies underscore the urgent need for innovative tools and approaches to improve audit outcomes.

Artificial Intelligence (AI) has emerged as a transformative technology with the potential to address many of the limitations of traditional auditing. AI tools such as machine learning algorithms, natural language processing, and robotic process automation can process large volumes of structured and unstructured data, detect anomalies, and provide auditors with predictive insights. Unlike traditional sampling techniques, AI can examine entire data sets, thereby enhancing the scope and reliability of audits. Moreover, by automating repetitive tasks, AI allows auditors to focus on higher-level risk analysis and professional judgment, ultimately improving efficiency. These advantages suggest that AI could significantly enhance both the quality and efficiency of auditing practices.

Despite these promising developments, several unresolved issues remain. First, there is limited empirical evidence, particularly in emerging economies like Nigeria, on the actual impact of AI adoption on audit outcomes. While global audit firms such as Deloitte, PwC, KPMG, and EY have begun integrating AI into their audit processes, many local and mid-tier firms continue to rely heavily on manual techniques. This disparity raises questions about whether AI-driven auditing is truly accessible, scalable, and effective in different organizational and regulatory contexts.

Second, concerns persist regarding the reliability and transparency of AI tools. Many AI systems operate as "black boxes," making it difficult for auditors to fully understand how conclusions are reached. This lack of transparency can undermine professional skepticism and accountability, especially if auditors become overly reliant on technology. Additionally, ethical and legal issues such as data privacy, cybersecurity risks, and algorithmic bias further complicate the adoption of AI in auditing.

Third, there is a growing concern about whether auditors possess the necessary skills to effectively deploy and interpret AI tools. The traditional accounting and auditing curriculum has not fully integrated technological competencies such as data analytics, machine learning, and AI applications. Without proper training and capacity building, auditors risk misapplying AI tools or misinterpreting their outputs, which could compromise audit quality instead of enhancing it.

Finally, regulatory and institutional frameworks have not kept pace with technological changes. In Nigeria, for example, neither the Financial Reporting Council (FRCN) nor the Institute of Chartered Accountants of Nigeria (ICAN) has developed comprehensive guidelines or standards on the use of AI in auditing. This regulatory gap creates uncertainty about how AI-driven audits should be conducted, documented, and evaluated, thereby raising questions about legal liability, professional responsibility, and audit assurance in the digital age.

In light of these concerns, the central problem this study seeks to address is the extent to which Artificial Intelligence improves audit quality and efficiency, and the challenges associated with its adoption in practice. While AI has been widely celebrated as a solution to the shortcomings of traditional auditing, there remains limited evidence on its practical impact, particularly in emerging economies where adoption is still at a developing stage. Without such evidence, auditors, regulators, and organizations risk either underutilizing AI's potential benefits or over-relying on it without fully addressing its limitations.

Therefore, this study is motivated by the need to empirically examine the impact of AI on audit quality and efficiency, while also identifying the barriers, risks, and implications of its adoption. By addressing this gap, the research will provide valuable insights for auditors, policymakers, and professional bodies seeking to harness the benefits of AI while maintaining audit integrity, independence, and public trust.

1.3 Research Questions

Flowing from the research gap, the following research question were raised

1. To what extent does Artificial Intelligence improve audit quality in terms of accuracy, reliability, and fraud detection?
2. How does the adoption of Artificial Intelligence influence audit efficiency with respect to time, cost, and resource utilization?

3. What challenges and limitations hinder the effective adoption of Artificial Intelligence in auditing practice?
4. How prepared are auditors in terms of skills, knowledge, and technological competence to effectively utilize AI tools in auditing?
5. What are the implications of Artificial Intelligence adoption for regulatory compliance, auditor independence, and professional ethics?

1.4 Research Objectives

1. To examine the extent to which Artificial Intelligence enhances audit quality in terms of accuracy, reliability, and error detection.
2. To evaluate the impact of Artificial Intelligence on audit efficiency with respect to time savings, cost reduction, and process automation.
3. To investigate the challenges and limitations associated with the adoption of Artificial Intelligence in auditing practice.
4. To assess the readiness of auditors in terms of skills, knowledge, and technological competence required for effective AI adoption.
5. To analyze the implications of Artificial Intelligence adoption for regulatory compliance, professional ethics, and auditor independence.

1.5 Research Hypotheses

1. Artificial Intelligence has no significant effect on audit quality in terms of accuracy, reliability, and fraud detection.
2. Artificial Intelligence adoption does not significantly influence audit efficiency in terms of time, cost, and resource utilization.
3. Challenges and limitations associated with AI adoption do not significantly affect its effectiveness in auditing practice.
4. Auditor preparedness in terms of skills, knowledge, and technological competence has no significant relationship with the effective use of AI in auditing.
5. Artificial Intelligence adoption has no significant implications for regulatory compliance, auditor independence, and professional ethics.

1.6 Scope of the Study

The scope of this study is defined to provide clarity on the boundaries within which the research will be conducted, ensuring focus, manageability, and relevance to the research objectives. Since Artificial Intelligence (AI) is a broad concept that spans multiple industries and applications, this research will specifically focus on its adoption and impact on auditor in Benin. The study will primarily examine the relationship between Artificial Intelligence and two key dimensions of auditing: audit quality and audit

efficiency. Audit quality will be assessed in terms of accuracy, reliability, fraud detection, and the ability of auditors to provide credible assurance. Audit efficiency will be examined in relation to time savings, cost reduction, and process automation. In addition, the study will consider secondary factors such as auditor preparedness, ethical implications, and regulatory issues associated with the adoption of AI in auditing practice. This research will be carried out within Nigeria, an emerging economy where the adoption of AI in auditing is still at a developing stage. While international firms such as the Big Four (KPMG, Deloitte, PwC, and EY) have already introduced AI into their auditing processes globally, local audit firms and practitioners in Nigeria are yet to fully embrace these innovations. By focusing on Nigeria, the study will capture the unique challenges and opportunities of AI adoption in an environment characterized by regulatory gaps, infrastructural limitations, and varying levels of technological readiness.

The study will target auditors working in both large audit firms (including multinational firms operating in Nigeria) and medium to small-sized indigenous audit practices. This inclusive approach will ensure a balanced perspective by comparing levels of AI adoption across different categories of audit firms. Additionally, the study will involve insights from professional accountants and auditors affiliated with regulatory and professional bodies such as the Institute of Chartered Accountants of Nigeria (ICAN) and the Financial Reporting Council of Nigeria (FRCN). The study will adopt a quantitative research design using survey questionnaires as the primary instrument for data collection.

Respondents will include practicing auditors, audit managers, and partners with direct experience in audit processes. Statistical tools such as descriptive statistics, correlation, and regression analysis will be employed to analyze the data and test the stated hypotheses. Where necessary, qualitative insights from interviews may be used to complement the quantitative findings. The research will focus on the period between 2018 and 2025, a timeframe during which AI applications in auditing began to gain momentum globally and locally. This period is particularly relevant given the increasing number of corporate scandals, heightened regulatory demands, and rapid digital transformation that have placed audit practices under greater scrutiny. While the study will explore the impact of AI on audit practice, it will not attempt to cover the broader impact of AI on other areas of accounting, such as taxation, management accounting, or financial advisory services. Similarly, the study will not focus on other emerging technologies such as blockchain, big data analytics, or cloud computing except where they intersect with AI in auditing. This delimitation ensures that the research remains focused on its central theme (Hasan, 2021).

1.7 Significance of the Study

The rapid advancement of technology in the 21st century has brought about profound changes in the field of auditing, with Artificial Intelligence (AI) emerging as one of the most transformative tools. This study is significant because it provides both theoretical and practical contributions to knowledge, professional practice, and policy development

in the auditing field. This research will enrich the existing body of literature on auditing and emerging technologies by providing empirical evidence on the impact of AI on audit quality and efficiency. While several studies in developed economies have examined the integration of AI in auditing, there remains a scarcity of empirical research in emerging economies such as Nigeria. By bridging this gap, the study will serve as a valuable resource for researchers, postgraduate students, and academics interested in technology adoption in auditing and accounting. For practicing auditors, both in local firms and international audit companies, the study offers insights into how AI tools can enhance accuracy, improve fraud detection, and increase efficiency in audit engagements. It highlights practical areas where AI can reduce the time spent on routine tasks, thereby allowing auditors to focus more on risk assessment and strategic decision-making. Furthermore, the findings will help auditors understand the challenges associated with AI adoption, such as skill requirements, costs, and ethical considerations, enabling them to develop strategies for effective implementation.

Professional accounting and auditing bodies such as the Institute of Chartered Accountants of Nigeria (ICAN), the Association of Chartered Certified Accountants (ACCA), and the International Federation of Accountants (IFAC) will benefit from the study by using its findings to review and update training curricula and professional development programs. By identifying the skills and competencies required to effectively utilize AI in auditing, this study will guide the development of new capacity-building

initiatives that prepare auditors for the demands of a technology-driven audit environment. Regulatory institutions such as the Financial Reporting Council of Nigeria (FRCN) and the Securities and Exchange Commission (SEC) will find the study useful in formulating policies and guidelines for the ethical and standardized adoption of AI in auditing practice. The research will shed light on the implications of AI for regulatory compliance, independence, and professional ethics, thereby helping regulators strike a balance between innovation and accountability. This is particularly important in preventing regulatory gaps that may arise from the rapid deployment of advanced technologies. For organizations that are the subject of audits, the adoption of AI-based auditing tools holds the potential to increase transparency, accountability, and investor confidence. By improving the speed and reliability of audit reports, AI enhances stakeholder trust in financial information, which in turn supports better decision-making, investment, and corporate governance. The findings of this study will provide organizations with an understanding of how AI adoption in auditing could affect the credibility of their financial reports and overall reputation in the marketplace.

At a broader level, the study is significant to society and the economy as a whole. High-quality and efficient audits contribute to financial stability, reduce the likelihood of corporate scandals, and protect the interests of investors and the general public. By exploring the role of AI in strengthening audit practice, this study indirectly supports economic growth, capital market stability, and sustainable business practices. In summary,

the significance of this study lies in its potential to provide a holistic understanding of the opportunities and challenges associated with Artificial Intelligence in auditing. It will contribute to academic discourse, inform professional practice, guide regulatory decisions, and promote stakeholder trust in financial reporting. Ultimately, the study will serve as a roadmap for navigating the evolving landscape of auditing in the digital era (Hasan, 2021).

CHAPTER TWO:

LITERATURE REVIEW

2.1 Concept of Audit Quality

2.1.1 Definition of Audit Quality

The concepts of audit quality and efficiency have long attracted scholarly attention because they are central to the credibility of financial reporting and the sustainability of auditing as a profession. While audit quality relates to the degree to which an audit enhances the reliability of financial information, audit efficiency refers to how well auditors can achieve such quality within reasonable limits of time and cost (Hasan, 2021). These two constructs are interlinked, yet tensions often arise when the pursuit of efficiency seems to compromise quality, or when quality improvements demand greater resource commitments. With the emergence of Artificial Intelligence (AI) and advanced analytics, the debate has intensified, as new technologies promise to improve both quality and efficiency simultaneously (Hasan, 2021).

Audit quality is a complex and multi-dimensional construct. According to DeAngelo (1981), audit quality is defined as the joint probability that an auditor will both (a) discover a breach in the accounting system and (b) report the breach. This foundational definition emphasizes two critical aspects: auditor competence (ability to detect misstatements) and auditor independence (willingness to disclose them). Over time, scholars have expanded this view. Francis (2011) presented a broader framework where

audit quality comprises three dimensions: Inputs Auditor expertise, firm resources, and adherence to standards. Processes Methodology, tools, and professional judgment applied during the audit. Outputs Audit opinions, reduced misstatements, restatements, and stakeholder confidence. In practice, regulators such as the International Auditing and Assurance Standards Board (IAASB, 2014) also emphasize ethics, professional skepticism, and compliance with International Standards on Auditing (ISAs) as core components of audit quality (Opuirobo, et al., 2025).

Measuring audit quality has been challenging because it is not directly observable. As a result, researchers and regulators rely on indirect proxies, including: Financial Restatements: Frequent restatements suggest low audit quality. Audit Firm Size: Large firms (Big Four) are often associated with higher quality due to global resources and reputation. Litigation and Regulatory Actions: Higher legal challenges suggest possible audit failures. Going Concern Opinions: Issuance of appropriate warnings is considered an indicator of quality. Stakeholder Perceptions: Surveys and interviews capturing confidence in audit reliability. Audit Fee Premiums: Higher fees may reflect greater audit effort and quality. However, each proxy has limitations. For instance, restatements may result from management fraud rather than audit negligence. This underlines the importance of adopting multi-dimensional frameworks in evaluating audit quality. Several factors influence the quality of audit outcomes: Auditor Competence and Training Professional skills, experience, and continuous education are vital. Audit Firm

Resources Access to modern tools, AI systems, and adequate staffing. Independence and Ethics Freedom from client pressure and ethical integrity. Regulatory Environment strong oversight bodies enhance discipline. Audit Methodology and Technology Use of advanced techniques, AI, and data analytics. Client Characteristics Complex operations and high-risk industries demand higher effort (Opuirobo, et al., 2025).

In developing economies like Nigeria, limited resources, regulatory gaps, and technological lag often hinder audit quality. Efficiency in auditing refers to the optimal use of time, cost, and resources in completing engagements without compromising quality. Knechel et al. (2012) define audit efficiency as maximizing desirable outputs (accuracy, insights, client satisfaction) relative to inputs (staff hours, costs, and technology). Efficiency is typically evaluated using: Audit Cycle Time The period between audit commencement and report issuance. Cost Control Reduction of unnecessary expenses without undermining audit rigor. Automation Levels Use of tools to streamline repetitive tasks such as data entry and reconciliations. Productivity Ratios Engagement hours versus number of reports issued.

In contemporary practice, efficiency has become a competitive differentiator for audit firms, as clients demand quicker yet reliable audits in an era of real-time financial reporting.

Audit quality and efficiency are often portrayed as competing objectives. High-quality audits may require significant time and resources, potentially reducing efficiency. Conversely, overly efficient audits may cut corners, leading to reduced quality. The challenge for auditors is therefore to strike a balance. However, recent advancements in AI and digital tools suggest that quality and efficiency can complement each other. For example: AI can perform full-population testing, enhancing accuracy (quality) while reducing manual effort (efficiency). Automated documentation reduces clerical workload, improving efficiency without lowering quality. Predictive analytics helps focus auditor attention on high-risk areas, simultaneously boosting quality and efficiency. Thus, technology if well implemented may help resolve the traditional trade-off. The significance of these concepts can be seen from three perspectives: For Stakeholders: High audit quality improves investor confidence, financial stability, and capital market efficiency. For Audit Firms: Efficiency enhances profitability, competitiveness, and client retention. For Regulators: Quality and efficiency ensure compliance, reduce financial scandals, and sustain the credibility of financial reporting.

Notably, in Nigeria and other developing economies, corporate failures such as Cadbury Nigeria Plc (2006) and Oceanic Bank (2009) highlight the devastating consequences of low audit quality, while client complaints about high fees and long delays stress the importance of efficiency. United States: The PCAOB emphasizes stricter standards and advanced audit technologies to ensure quality post-Enron and WorldCom scandals.

Europe: The EU Audit Reform (2016) introduced audit rotation and enhanced transparency reporting. Asia: China and India encourage AI adoption in audits to cope with large corporate bases and data-driven economies. Africa: Limited adoption of AI and weak enforcement of standards constrain both audit quality and efficiency. The integration of AI, blockchain, and advanced analytics is transforming both quality and efficiency. Machine Learning (ML) improves fraud detection accuracy. Natural Language Processing (NLP) enables automated contract and document review. Robotic Process Automation (RPA) accelerates reconciliations and report generation. Blockchain-based auditing allows real-time transaction verification. Thus, technology is no longer optional but necessary to sustain both audit quality and efficiency. Despite its importance, the literature on audit quality and efficiency faces criticism: Ambiguity in Measurement: No universally accepted metric. Contextual Differences: What defines quality in developed economies may differ in developing economies. Technology Dependence: Over-reliance on AI may undermine auditor judgment. Cost Implications: Efficiency gains from technology may be offset by high acquisition costs in low-resource environments.

The concepts of audit quality and efficiency are foundational to modern auditing. While historically perceived as competing objectives, technological advancements especially AI have redefined them as potentially complementary. In the Nigerian context, achieving both remains challenging due to skill gaps, cost barriers, and regulatory shortcomings. Nonetheless, as global auditing moves toward technology-driven approaches, auditors

must adopt strategies that optimize both quality and efficiency without compromising professional skepticism, independence, or ethical standards.

2.2 Overview of Artificial Intelligence in Auditing

Artificial Intelligence (AI) has emerged as a transformative force across industries, and the auditing profession is no exception. The increasing complexity of business transactions, vast volumes of data, and heightened stakeholder expectations have necessitated innovative solutions beyond traditional audit techniques. Auditing, which historically relied on manual sampling, judgment, and standardized procedures, is gradually embracing AI tools such as machine learning, natural language processing, robotic process automation, and predictive analytics. In the auditing context, AI is defined as the simulation of human intelligence processes by computer systems to analyze financial data, identify anomalies, detect fraud, and improve decision-making with minimal human intervention. The adoption of AI in auditing is driven by the dual objectives of enhancing audit quality (accuracy, reliability, fraud detection) and audit efficiency (reducing time, costs, and resource constraints).

The role of technology in auditing has evolved over decades: Traditional Auditing (Pre-1990s): Reliance on manual verification, vouching, and limited sampling. Computer-Assisted Audit Techniques (1990s–2000s): Introduction of audit software like ACL and IDEA for sampling and data analysis. Data Analytics and Continuous Auditing (2010s):

Real-time monitoring and trend analysis using large datasets. Artificial Intelligence Era (2020s onwards): Integration of advanced algorithms that enable full-population testing, predictive risk assessment, and cognitive analytics. Global audit firms (the "Big Four") have pioneered AI-driven solutions, with Deloitte's "Argus," PwC's "GL.ai," KPMG's "Clara," and EY's "Helix" serving as industry benchmarks. AI in auditing is not a single technology but a collection of interrelated innovations: Machine Learning (ML): Algorithms that learn from past financial data to detect anomalies and predict risks (e.g., unusual journal entries, fraudulent invoices). Natural Language Processing (NLP): Enables auditors to analyze unstructured data such as contracts, emails, and board minutes. Robotic Process Automation (RPA): Automates repetitive audit tasks like data extraction, reconciliations, and confirmations. Predictive and Prescriptive Analytics: Forecasts potential misstatements or fraud scenarios and suggests audit procedures. Cognitive Computing: Mimics human judgment in interpreting ambiguous data, useful in evaluating complex estimates like goodwill impairment. Blockchain Integration with AI: Enhances transaction verification, ensuring transparency and accuracy.

These tools collectively enhance both the depth (quality) and breadth (efficiency) of audit procedures. AI applications span the entire audit cycle: Risk Assessment: AI helps auditors identify high-risk transactions and accounts, reducing reliance on random sampling. Substantive Testing: Instead of testing a subset, AI enables analysis of the full dataset, increasing audit assurance. Fraud Detection: Machine learning algorithms

identify patterns indicative of fraud, such as round-dollar payments or duplicate vendor accounts. Compliance Monitoring: AI systems track regulatory requirements and flag deviations in financial reporting. Audit Documentation: RPA generates automated working papers, improving efficiency in record-keeping. Client Advisory: AI-driven insights help auditors provide value-added services, such as business performance analysis. For example, PwC's GL.ai reviews millions of journal entries in seconds, highlighting unusual postings that may indicate misstatements or fraud. This not only saves time but also enhances the detection of risks that manual methods may overlook.

The integration of AI offers numerous advantages: Enhanced Audit Quality: Comprehensive data analysis reduces the probability of undetected misstatements. Improved Efficiency: Automation reduces audit cycle times and costs. Scalability: AI can handle large, complex datasets from multinational corporations. Continuous Auditing: AI enables real-time transaction monitoring, providing assurance beyond the year-end audit. Fraud Detection and Prevention: Sophisticated algorithms enhance the detection of red flags that traditional sampling misses. Value Addition: AI frees auditors from routine tasks, allowing them to focus on judgment, interpretation, and advisory roles. Despite its promise, AI adoption faces several obstacles: Cost of Implementation: AI systems require significant financial investment, often beyond the reach of small audit firms. Skill Gaps: Many auditors lack expertise in data science, limiting effective AI usage. Over-Reliance on Technology: Excessive dependence may reduce professional skepticism and critical

judgment. Data Privacy and Security Risks: AI systems handle sensitive client data, increasing vulnerability to cyberattacks. Regulatory Uncertainty: Lack of global standards for AI auditing practices hinders consistent application. Ethical Considerations: Questions arise regarding transparency, accountability, and auditor independence when decisions are heavily automated. For example, in Nigeria, many audit firms face challenges related to cost, infrastructure, and inadequate auditor training in AI systems. Developed Economies: The U.S. and EU have integrated AI extensively, driven by regulatory expectations (e.g., PCAOB, EU Audit Reform). Emerging Economies: Countries like China and India are rapidly scaling AI in auditing due to the high volume of corporate data. Africa and Nigeria: Adoption remains slow due to high costs, inadequate infrastructure, and limited regulatory guidance. However, increasing corporate scandals and demand for audit credibility are pushing firms toward gradual AI adoption (Davies, et al.,2025).

The future of auditing is likely to be hybrid, where human auditors collaborate with AI systems: Auditors will shift from manual verification to judgment-oriented roles, focusing on interpretation, ethics, and advisory services. AI will provide continuous assurance, detecting anomalies in real-time instead of post-transaction review. Regulators are expected to introduce AI auditing standards, ensuring consistency and accountability. Universities and professional bodies (ACCA, ICAN, ICAEW) are integrating AI training into curricula to bridge the skill gap. Ultimately, the profession is moving toward what

scholars describe as the “augmented auditor” model a professional empowered by AI rather than replaced by it. Artificial Intelligence represents a paradigm shift in auditing practice. By enhancing both audit quality and efficiency, AI addresses the limitations of traditional auditing methods (Davies, et al.,2025). Its applications from risk assessment to fraud detection and compliance monitoring demonstrate its transformative potential. However, challenges relating to cost, skills, ethics, and regulation must be addressed to fully realize its benefits. For countries like Nigeria, where corporate governance issues and financial reporting failures remain pressing concerns, AI adoption could significantly strengthen audit credibility. Yet, this requires deliberate investment in technology, regulatory support, and auditor capacity-building.

2.3 Empirical Studies on AI and Auditing

Empirical studies provide evidence-based insights into how Artificial Intelligence (AI) impacts auditing in practice. While conceptual discussions highlight the potential benefits of AI in enhancing audit quality and efficiency, it is through empirical investigations field surveys, interviews, case studies, and archival analyses that the practical relevance of AI in auditing is fully demonstrated. This section reviews empirical studies from both developed and developing economies, highlighting the opportunities, challenges, and trends in AI adoption. Several studies in the U.S. and Europe have examined the integration of AI into audit practices, especially among the Big Four firms (Davies, et al.,2025).

Issa, Sun, and Vasarhelyi (2016) conducted case studies of Big Four audit firms, finding that AI tools such as machine learning and natural language processing significantly improved fraud detection and anomaly identification. Kokina and Davenport (2017) surveyed 120 auditors in the U.S. and found that 78% believed AI enhances audit efficiency, while 65% acknowledged its potential to increase audit quality. However, a lack of adequate training remained a major barrier. Brown-Liburd, Issa, and Lombardi (2019) examined how auditors perceive AI-driven decision support systems. Their experimental results indicated that auditors using AI-assisted tools identified 25% more anomalies compared to those using traditional audit software. PwC's GL.ai system was evaluated in a case study by Rozario and Vasarhelyi (2018). The study showed that AI identified unusual journal entries across millions of transactions, a task that would have taken auditors months.

Liu et al. (2020) studied AI adoption among Chinese auditing firms, reporting that AI improved audit accuracy by 40%, particularly in fraud-prone industries. However, smaller firms struggled with the financial cost of AI implementation. Gupta and Sharma (2021) analyzed AI's role in India's audit sector and found that while efficiency increased significantly, regulatory uncertainty discouraged widespread adoption. In Japan, Kato (2019) surveyed auditors and concluded that AI tools reduced routine workload by up to 50%, allowing auditors to focus on judgmental aspects such as assessing management estimates.

Empirical evidence from developed economies strongly supports the argument that AI improves audit quality and efficiency. However, challenges around costs, regulation, and auditor skills persist. In Africa, empirical studies are fewer but growing, largely focusing on Nigeria and South Africa. Owolabi and Dada (2020) conducted a survey of 150 Nigerian auditors, revealing that only 28% of firms used AI tools. Despite limited adoption, 82% of respondents agreed that AI has the potential to improve fraud detection and audit efficiency. Chinedu and Ugochukwu (2021) carried out interviews with Nigerian audit managers and found that most firms lacked the financial capacity to invest in AI technologies. However, those using basic AI-enabled data analytics reported improved detection of irregularities. Nkosi (2019) studied South African auditors and highlighted that firms using AI tools experienced reduced audit completion time by an average of 35%. Githae and Karanja (2022) in Kenya reported that AI-driven audit tools were mainly adopted by multinational audit firms, with local firms lagging due to infrastructure and cost barriers. Al-Harbi (2021) studied AI in Saudi Arabia's auditing sector and found that adoption was growing due to regulatory encouragement. AI systems enhanced risk assessment accuracy but faced resistance from traditional auditors who feared job displacement.

2.3.1 Comparative Summary of Empirical Studies

Author(s) & Year	Country/Region	Methodology	Findings	Challenges
Issa et al. (2016)	USA	Case study (Big Four)	AI improved fraud detection & anomaly identification	Skill gap among auditors
Kokina & Davenport (2017)	USA	Survey (120 auditors)	AI enhanced efficiency & quality	Lack of training
Brown-Liburd et al. (2019)	USA	Experiment	AI users detected 25% more anomalies	Reliance on AI
Liu et al. (2020)	China	Survey	Audit accuracy improved by 40%	High costs
Gupta & Sharma (2021)	India	Interviews	Efficiency gains	Regulatory uncertainty
Kato (2019)	Japan	Survey	Workload reduced by 50%	Ethical concerns
Owolabi & Dada (2020)	Nigeria	Survey (150 auditors)	Only 28% adoption; strong potential for quality improvement	Cost, infrastructure
Nkosi (2019)	South Africa	Mixed methods	35% reduction in audit time	Resistance from smaller firms
Al-Harbi (2021)	Saudi Arabia	Survey	Improved risk assessment	Auditor resistance

Researchers Compilation

Themes Emerging from Empirical Evidence

From reviewing these studies, several key themes emerge: Most studies (Issa et al., 2016; Liu et al., 2020; Owolabi & Dada, 2020) confirm that AI improves audit quality through enhanced anomaly detection, better fraud identification, and more reliable audit evidence. AI reduces audit time and cost (Nkosi, 2019; Kato, 2019). This is particularly important for large audits with complex datasets. High implementation costs, lack of technical expertise, regulatory uncertainty, and resistance from auditors are common challenges (Gupta & Sharma, 2021; Al-Harbi, 2021). Developed economies show higher adoption rates, with Big Four firms leading the way. Developing economies like Nigeria show limited adoption but strong recognition of potential benefits. Several studies highlight a movement toward continuous auditing, AI-driven fraud prevention, and augmented auditor roles. The review of empirical studies provides important insights for this project: There is a clear consensus that AI enhances both audit quality and efficiency, but adoption is uneven across regions. While developed economies provide strong empirical evidence of AI's benefits, developing economies face barriers that limit AI adoption. In Nigeria, very few empirical studies exist, creating a research gap that this study aims to fill. The findings from prior studies suggest that if properly implemented, AI can significantly improve audit outcomes in Nigeria, but cost, training, and regulatory support must be addressed. Empirical studies across the globe provide strong evidence that AI has transformative potential in auditing. While developed economies have already embraced

AI, developing countries like Nigeria are still in the early stages of adoption. The findings reveal a consistent pattern: AI improves audit quality and efficiency but faces significant challenges relating to costs, auditor competence, infrastructure, and regulation. This body of literature justifies the need for further research into the Nigerian auditing context, where empirical data is limited but where the potential for AI to address audit quality failures is immense.

2.4 Theories Related to Auditing

The practice of auditing is grounded in several theoretical frameworks that explain its purpose, functions, and effectiveness. These theories provide the foundation for understanding auditor behavior, the expectations of stakeholders, and the mechanisms through which auditing enhances accountability, trust, and transparency. In the context of emerging technologies such as Artificial Intelligence (AI), these theories help to explain how technological changes may reshape audit processes and outcomes. This section discusses five key theories related to auditing: Agency Theory, Stakeholder Theory, Fraud Triangle Theory, Institutional Theory, and the Technology Acceptance Model (TAM).

2.4.2 Agency Theory

Agency theory, introduced by Jensen and Meckling (1976), has become a cornerstone in corporate governance and auditing literature. It explains the contractual relationship between principals (shareholders) and agents (management), where agents are entrusted

with decision-making authority but may not always act in the best interests of principals. This divergence of interests gives rise to agency problems, such as information asymmetry, opportunistic behavior, moral hazard, and adverse selection. Auditing serves as a mechanism to minimize these conflicts by providing independent assurance that financial statements prepared by management reflect the true financial position of the organization. In the 21st century, technological advancements, particularly Artificial Intelligence (AI), are reshaping how audits are conducted. AI enhances audit quality by improving accuracy, fraud detection, transparency, and efficiency thereby strengthening the agency relationship. This section explores the relevance of Agency Theory to auditing, and how AI directly impacts audit quality by addressing key challenges within the principal-agent framework. Agency theory emphasizes two central problems in the relationship between principals and agents: Conflict of Interest: Managers may prioritize personal gains (e.g., bonuses, perks, or job security) over shareholder value. For example, inflating revenues or hiding liabilities to appear profitable. Information Asymmetry: Managers typically have more knowledge about the firm's financial activities than shareholders, which can be exploited to misrepresent financial performance.

Auditors act as intermediaries who reduce these problems by ensuring credibility of financial reporting. Independent audits provide assurance that financial statements are free from material misstatements, whether due to fraud or error. External audits reduce agency costs by ensuring managers present reliable financial statements. Audit opinions

serve as a trust signal for investors, creditors, regulators, and other stakeholders. Auditing ensures that managers are accountable for the resources entrusted to them. However, traditional audit methods often rely on sampling and manual judgment, which may fail to detect subtle manipulations, especially in large data environments. This limitation reinforces the need for technological interventions such as AI. AI technologies such as machine learning, natural language processing, robotic process automation, and predictive analytics strengthen auditing's role in reducing agency conflicts. Their impacts on audit quality can be analyzed through the lens of agency theory:

Traditionally, managers could exploit gaps in auditor knowledge or hide irregularities in massive datasets. AI systems enable continuous auditing by analyzing 100% of transactions rather than relying on limited samples. This reduces the informational advantage that managers hold over shareholders, closing the asymmetry gap. Example: In Nigerian banks, AI-driven audit tools can flag suspicious loan classifications or hidden liabilities in real time. Audit quality improves when errors and fraud are detected more effectively. AI algorithms identify patterns, anomalies, and outliers that may escape human detection. By increasing accuracy, auditors provide stronger assurance to principals that agents' financial reports are trustworthy.

Managers sometimes manipulate accounts to maximize bonuses or meet market expectations. AI, combined with forensic auditing techniques, helps identify subtle earnings management practices such as round-trip transactions, inflated asset valuations,

or unusual journal entries. For instance, machine learning models can compare a firm's reporting patterns with industry norms to detect deviations suggestive of manipulation. Human auditors may face bias, fatigue, or undue influence from management. AI-based systems reduce dependence on human discretion, ensuring more consistent and objective audit procedures. This strengthens the monitoring function and addresses agency conflicts where management seeks to influence audit outcomes. AI-enabled dashboards provide real-time audit insights to both auditors and stakeholders. This reduces the time lag between financial misrepresentation and detection, reinforcing management's accountability. Transparent reporting aligns with agency theory's goal of minimizing hidden actions by agents. AI equips auditors with advanced tools to monitor agent behavior more effectively. Auditors move from a reactive role (detecting fraud after occurrence) to a proactive role (predicting and preventing misrepresentation).

Greater assurance on audit quality boosts investor confidence and reduces the perceived risk of investing. Agency costs (e.g., monitoring expenditures, loss from misreporting) are significantly reduced. Knowing that AI-driven audits can detect anomalies discourages opportunistic behaviors. However, managers may resist AI adoption if they fear it increases scrutiny. While AI significantly improves audit quality under the agency theory lens, some challenges exist: Over-reliance on Technology Excessive dependence on AI may undermine auditor judgment. Data Privacy and Security Risks Continuous auditing requires access to sensitive information. Skill Gap Auditors need new

competencies to interpret AI results effectively. Bias in Algorithms If training data is biased, AI outcomes may be flawed, affecting audit quality. Thus, while AI enhances the monitoring role in agency relationships, its effectiveness depends on ethical use, auditor competence, and robust regulatory frameworks.

Big Four Audit Firms: Deloitte and PwC use AI-driven platforms such as Argus and Halo to analyze complete datasets, reducing managers' ability to hide fraudulent transactions. Nigeria's Banking Sector: AI adoption in internal auditing has improved detection of insider-related loans and reduced information asymmetry between bank executives and regulators.

Global Scandals: The collapse of Enron and Wirecard highlighted agency problems. AI could have detected suspicious accounting practices earlier, strengthening audit quality. Agency theory highlights the conflicts of interest and information asymmetry inherent in the principal-agent relationship. Auditing acts as a monitoring mechanism to address these issues, but traditional methods have limitations in large, complex business environments.

2.4.3 Stakeholder Theory

Auditing is a critical mechanism for building trust in financial reporting, enhancing accountability, and safeguarding the interests of multiple parties. While traditional audit frameworks often emphasized the principal–agent relationship between shareholders and

management, the emergence of stakeholder theory has broadened the scope of accountability. Introduced by Freeman (1984), stakeholder theory argues that organizations have obligations not only to shareholders but also to a wide array of stakeholders such as employees, regulators, customers, creditors, and society at large. In the auditing profession, this perspective means that auditors are expected to provide assurance that financial statements are fair, reliable, and transparent in order to protect the interests of these diverse groups. With the rise of Artificial Intelligence (AI) in auditing, stakeholder expectations have intensified. Stakeholders increasingly demand faster audits, higher detection of irregularities, reduced audit failures, and greater transparency in corporate reporting. This section explores stakeholder theory in relation to AI adoption and its implications for audit quality.

Stakeholder theory challenges the narrow shareholder-centric view of corporate governance. It asserts that: Multiple stakeholders have legitimate claims on the organization. Organizations must balance competing interests to achieve long-term success. Decision-making must consider ethical and social responsibilities in addition to financial objectives. For auditors, this means that their work cannot only serve shareholders but must also provide confidence to regulators, employees, creditors, and the wider society. High-quality audits are therefore essential to maintain stakeholder trust. Application of Stakeholder Theory to Auditing, Audit quality is multi-dimensional and reflects the ability of auditors to detect material misstatements, adhere to professional

standards, and provide reliable assurance to diverse stakeholder groups. From a stakeholder theory perspective: Shareholders demand accurate and transparent financial reporting to make informed investment decisions. Regulators (e.g., SEC, FRC, ICAN in Nigeria; PCAOB internationally) require compliance with legal and professional standards. Employees rely on credible audits for job security and fair performance assessments. Creditors and investors depend on audited reports to evaluate solvency and repayment capacity. The wider public and society expect auditors to prevent corporate scandals that could harm communities and economies. Thus, audit quality becomes the mechanism through which auditors fulfill their responsibility to stakeholders. Weak audits, such as those preceding the collapse of Enron, WorldCom, or Nigerian bank failures, erode stakeholder trust and damage the legitimacy of the audit profession.

The integration of AI into auditing significantly changes how auditors respond to stakeholder needs. AI tools such as machine learning algorithms, natural language processing, predictive analytics, and robotic process automation (RPA) offer auditors advanced capabilities to analyze vast datasets, detect anomalies, and conduct real-time monitoring. From a stakeholder perspective, these technologies bring both opportunities and challenges: AI systems can examine 100% of financial transactions, thereby reducing sampling risks. This gives shareholders more reliable assurance compared to traditional audit methods. Regulators emphasize compliance and audit transparency. AI allows auditors to provide audit trails, automated documentation, and continuous reporting

improving regulatory oversight and confidence. Predictive analytics enhances auditors' ability to forecast financial risks and detect fraud, giving lenders and investors stronger assurance in credit and investment decisions. In light of repeated financial scandals, the public expects auditors to act as gatekeepers. AI strengthens the capacity of auditors to detect fraudulent schemes, thereby protecting communities from the adverse effects of corporate collapse. Despite these advantages, AI adoption also raises stakeholder concerns: Over-reliance on automated tools may undermine auditor judgment. Ethical questions emerge around data privacy and algorithmic bias. Smaller audit firms may lack the resources to adopt AI, potentially widening the gap between large and small firms, thus disadvantaging some stakeholder groups. Stakeholder theory highlights that audit quality is not only a technical measure but also a relational and ethical issue. High-quality audits strengthen stakeholder trust by ensuring: Transparency AI improves disclosure by identifying hidden patterns in data. Timeliness Continuous auditing facilitated by AI provides stakeholders with up-to-date information. Accountability Enhanced fraud detection ensures managers are held accountable. Equity AI can reduce bias in audit sampling, benefiting all stakeholders equally. For example, Nigerian regulators (such as the Financial Reporting Council) have stressed the need for AI-driven analytics to improve oversight of listed companies. Similarly, the Big Four audit firms globally are heavily investing in AI platforms like EY Helix, KPMG Clara, and Deloitte Omnia, designed to improve audit quality in response to stakeholder pressure. Stakeholder theory

underscores the importance of considering multiple parties in the auditing process, not just shareholders. In the era of Artificial Intelligence, auditors face heightened expectations to deliver audits that are accurate, timely, transparent, and socially responsible. AI provides powerful tools to meet these demands, but its adoption also raises new ethical and professional challenges that must be carefully managed.

Ultimately, by integrating AI in ways that align with stakeholder interests, the auditing profession can enhance audit quality and restore public confidence in financial reporting. Thus, stakeholder theory provides a vital lens for understanding the evolving relationship between AI, audit quality, and the broader accountability of auditors to society.

2.4.4 Fraud Triangle Theory

The Fraud Triangle Theory, developed by Donald Cressey (1953), is one of the most widely recognized frameworks for explaining why individuals commit fraud within organizations. According to the theory, three conditions must be present for fraud to occur: pressure (or incentive), opportunity, and rationalization. Over the years, auditors and researchers have relied on this framework to assess fraud risk and design effective audit procedures. However, with the advent of Artificial Intelligence (AI) in auditing, the way auditors apply and interpret the Fraud Triangle has changed significantly (Gupta, et al.,2021).

AI technologies, such as machine learning, natural language processing, and robotic process automation, enhance audit quality by providing stronger fraud detection mechanisms, reducing opportunities for fraud, and offering auditors deeper insights into organizational risk. This section explores how the Fraud Triangle Theory relates to the impact of AI on audit quality, highlighting its implications for fraud detection, prevention, and overall audit effectiveness (Gupta, et al.,2021).

The Fraud Triangle Theory proposes that fraud occurs when three factors converge: Pressure (or Incentive): This refers to financial or non-financial motivations that drive individuals to commit fraud. Examples include personal financial distress, unrealistic performance targets, or pressure to maintain corporate profitability. Opportunity: This arises when internal controls are weak, oversight is inadequate, or there are loopholes in monitoring systems. Fraud perpetrators exploit these weaknesses to conceal their actions. Rationalization: This refers to the psychological justification that fraudsters use to legitimize their unethical actions. For instance, an employee might rationalize theft by believing they are underpaid or that "everyone else is doing it." Auditors traditionally evaluate these three dimensions during risk assessment and fraud detection procedures (Gupta, et al.,2021). However, human limitations in detecting complex fraud schemes often leave gaps. This is where Artificial Intelligence offers transformative potential. AI-driven audit systems can analyze patterns in financial and non-financial data to identify signs of financial stress or unusual pressure points within organizations. For example:

Machine learning models can detect aggressive revenue recognition practices that suggest management is under pressure to meet earnings targets. Predictive AI tools can analyze employee expense claims, payroll anomalies, or unusual vendor transactions that reflect financial strain. By proactively identifying pressure points, AI enables auditors to focus on areas where fraud risk is elevated, thereby enhancing audit quality. The "opportunity" element of the Fraud Triangle is most directly influenced by AI technologies. Fraud thrives when controls are weak, but AI strengthens the control environment in several ways: Continuous Auditing: AI allows real-time monitoring of transactions, reducing the window of opportunity for fraudulent activities to go undetected. Anomaly Detection: Advanced algorithms can identify unusual transactions, duplicate payments, or round-dollar entries that human auditors might miss. Access Control Monitoring: AI systems can track user behavior and flag suspicious login attempts or unauthorized access to sensitive financial systems (Gupta, et al.,2021).

For example, banks employing AI-based fraud detection systems can instantly flag suspicious account activities, thereby reducing the opportunity for prolonged embezzlement or insider fraud. This enhanced control environment directly improves audit quality by ensuring that material misstatements due to fraud are detected earlier and with greater accuracy. Rationalization is psychological, making it difficult for auditors to observe directly. However, AI assists by providing objective evidence that undermines rationalization: Behavioral Analytics: AI tools can assess communication patterns (e.g.,

emails, chat logs) to detect changes in tone or language associated with unethical justification. Sentiment Analysis: Natural Language Processing (NLP) can analyze employees' justifications for unusual transactions, flagging cases where rationalizations may be masking fraud. Forensic AI Applications: These tools create a data-driven audit trail that makes it harder for individuals to rationalize fraudulent behavior when confronted with factual evidence. By offering clear, indisputable insights, AI strengthens the auditor's ability to challenge rationalizations that fraudsters rely upon. The integration of AI into auditing, guided by the Fraud Triangle Theory, significantly enhances audit quality in four key areas: AI improves the precision of fraud detection by reducing reliance on sampling. Entire datasets can be analyzed rather than subsets, increasing the likelihood of uncovering irregularities. AI tools provide consistent monitoring that is not subject to human fatigue or bias, enhancing the reliability of audit outcomes. By automating repetitive tasks, AI frees auditors to focus on higher-level judgmental issues, making the audit process more efficient without compromising quality. The greatest benefit lies in fraud detection. AI not only identifies anomalies but also predicts where fraud risks are likely to emerge, transforming audits from reactive to proactive processes (Gupta, et al.,2021). Financial Institutions: Many global banks use AI-powered fraud detection tools that analyze millions of transactions in real time. These tools drastically reduce opportunities for fraudulent activity, addressing a core element of the Fraud Triangle. Public Sector Auditing: In government auditing, AI has been deployed to detect

procurement fraud by identifying collusive bidding patterns or inflated contract values, reducing the opportunity for fraud. Corporate Auditing: AI has been applied in corporate settings to monitor journal entries and identify fraudulent revenue recognition practices driven by performance pressures. This aligns directly with the "pressure" side of the Fraud Triangle. These real-world applications highlight how AI operationalizes the Fraud Triangle, making audits more effective and credible. While AI strengthens audit quality through the Fraud Triangle lens, challenges remain: Over-Reliance on Technology: Auditors must avoid blind reliance on AI outputs, as algorithms may contain biases. Data Privacy Concerns: Collecting and analyzing vast datasets raises ethical and legal questions. Skill Gaps: Auditors require advanced technological competencies to interpret AI-driven fraud insights effectively. Despite these limitations, the benefits of integrating AI with Fraud Triangle assessments far outweigh the drawbacks, especially in reducing fraud risks and improving audit assurance. The Fraud Triangle Theory remains a cornerstone of auditing, providing insight into why individuals commit fraud (Gupta, et al.,2021). However, its application in practice has been significantly enhanced by Artificial Intelligence. AI technologies mitigate pressure, reduce opportunity, and challenge rationalization, thereby strengthening auditors' ability to detect and prevent fraud. By embedding the Fraud Triangle into AI-powered audit processes, audit quality is improved through greater accuracy, reliability, efficiency, and proactive fraud detection. In the era of digital transformation, the Fraud Triangle and AI together represent a

powerful synergy that redefines the scope and effectiveness of auditing. This integration not only addresses the timeless challenge of fraud but also positions auditors as trusted guardians of corporate integrity in an increasingly complex financial landscape (Gupta, et al.,2021).

2.4.5 Institutional Theory

Institutional theory explains how organizational practices and decisions are shaped not only by technical efficiency but also by the desire to conform to the norms, rules, and expectations of the wider institutional environment. It emphasizes that organizations often adopt certain practices to maintain legitimacy, gain social approval, and ensure survival in competitive environments (Meyer & Rowan, 1977; DiMaggio & Powell, 1983).

In auditing, institutional theory provides a framework for understanding why audit firms adopt new technologies, comply with regulatory standards, and align their practices with societal and professional expectations. The introduction of Artificial Intelligence (AI) into auditing processes can be interpreted as a response to institutional pressures both coercive (regulations), mimetic (imitation of industry leaders), and normative (professional standards).

According to DiMaggio and Powell (1983), institutional pressures manifest in three major forms: Coercive Pressures These arise from regulatory authorities, government mandates, and legal requirements. In auditing, standards such as International Standards on Auditing (ISA), IFRS, PCAOB regulations, and ICAN/ANAN guidelines in Nigeria push firms to maintain transparency and accountability. With growing demand for digital transformation, regulatory bodies indirectly coerce auditors to adopt AI for fraud detection, risk assessment, and compliance monitoring. Mimetic Pressures Organizations often imitate the practices of successful competitors to maintain legitimacy. The Big Four audit firms (PwC, KPMG, Deloitte, EY) have pioneered AI-based auditing tools such as PwC's GL.ai, Deloitte's Argus, and KPMG's collaboration with IBM's Watson. Smaller firms, in turn, feel pressured to adopt similar technologies to avoid being perceived as outdated or less credible. Normative Pressures – Professional associations and educational institutions create standards and norms that shape auditing practices. Institutions such as ICAN in Nigeria, ACCA in the UK, and AICPA in the USA emphasize continuous professional development, requiring auditors to adapt to technological change. Normative pressures therefore push auditors to embrace AI to maintain professional competence and relevance. The integration of AI into auditing processes can be seen as an organizational response to institutional demands for greater audit quality, transparency, and efficiency. Institutional theory suggests that audit firms may not always adopt AI solely because of internal cost-benefit analysis, but because

failing to do so risks loss of legitimacy in the eyes of clients, regulators, and the public (Gupta, et al.,2021).

Audit Quality Enhancement: Regulators and investors demand reliable and accurate financial statements. AI tools, such as machine learning and natural language processing, allow auditors to analyze entire data populations rather than samples, thereby improving accuracy and reducing audit risk. Risk of Non-Adoption: Firms that resist adopting AI may be perceived as lagging behind, undermining their credibility and competitiveness. In this sense, institutional legitimacy not just efficiency drives technology adoption. Institutional Diffusion: As AI becomes a recognized standard in global auditing practice, institutional pressures will accelerate its diffusion even in developing economies like Nigeria. Audit quality, as defined by DeAngelo (1981), is the probability that auditors both detect and report material misstatements. Institutional theory links AI adoption to audit quality improvement in several ways: AI-powered tools enhance compliance with international auditing standards by providing real-time monitoring, automated documentation, and precise error detection. Example: AI applications help auditors comply with ISA 240 (responsibility for detecting fraud) by identifying suspicious transactions across vast datasets. Professional bodies demand that auditors update skills in data analytics and AI. This ensures that the quality of audits meets current professional expectations. As auditors integrate AI, audit quality improves due to reduced human bias, enhanced judgment, and data-driven assurance. When leading audit firms deploy AI

successfully, others are compelled to follow suit to remain competitive. As AI becomes industry best practice, clients begin to expect AI-enhanced audit processes, which reinforces the link between institutional legitimacy and perceived audit quality. In Nigeria, institutional pressures are particularly evident: Regulatory Environment: Bodies such as the Financial Reporting Council of Nigeria (FRCN) and the Securities and Exchange Commission (SEC) increasingly emphasize accountability, making AI-driven auditing attractive for compliance. Professional Bodies: The Institute of Chartered Accountants of Nigeria (ICAN) and Association of National Accountants of Nigeria (ANAN) encourage members to embrace technology-driven audit practices to maintain relevance in the digital economy. Competitive Pressures: Nigerian subsidiaries of the Big Four firms already use AI-enabled tools, which creates pressure on medium-sized and local firms to adopt similar technologies to preserve legitimacy and client trust.

Thus, institutional theory explains why Nigerian auditors, even when resource-constrained, feel compelled to gradually adopt AI in order to maintain audit quality and align with international standards. While institutional theory provides useful insights, it has limitations: It tends to overemphasize conformity, neglecting cases where organizations innovate beyond institutional pressures. Adoption of AI may not always lead to real improvements in audit quality if firms only adopt it symbolically ("ceremonial adoption") to satisfy regulators. Resource limitations, especially in developing economies, may restrict adoption despite institutional pressures. Institutional

theory offers a compelling explanation for the adoption of AI in auditing, particularly in relation to audit quality. Audit firms face regulatory, professional, and competitive pressures that compel them to embrace AI technologies, even when adoption is costly or disruptive. By conforming to institutional demands, firms strengthen their legitimacy, ensure compliance, and enhance audit quality in the eyes of stakeholders (Gupta, et al.,2021).

In the Nigerian context, institutional theory suggests that AI adoption is not merely a matter of efficiency but also of survival, reputation, and professional relevance. Thus, AI serves as both a technical tool and an institutional response, reinforcing the importance of legitimacy in driving innovation in auditing practice.

Technology Acceptance Model (TAM)

The rapid integration of Artificial Intelligence (AI) into auditing has raised critical questions about how auditors perceive, accept, and effectively use these technologies. While AI promises to enhance audit quality through improved accuracy, fraud detection, and efficiency, its benefits largely depend on how auditors adopt and apply it in practice. The Technology Acceptance Model (TAM), developed by Davis (1989), provides a useful framework for understanding auditor behavior in relation to new technologies. The model posits that two main factors Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) determine the intention to use a system, which in turn influences actual system

adoption. By applying TAM to auditing, we can evaluate the extent to which auditors' perceptions of AI drive or hinder its adoption, thereby shaping its impact on audit quality. This section explores TAM in depth, its constructs, and how it relates to AI adoption in auditing (Gupta, et al.,2021).

The Technology Acceptance Model is an adaptation of the Theory of Reasoned Action (TRA), which links beliefs, attitudes, and behaviors. Davis (1989) introduced TAM to explain why individuals accept or reject technology. The model emphasizes three major components: Perceived Usefulness (PU): The degree to which a person believes that using a particular system will enhance job performance. In auditing, PU may refer to whether AI improves the accuracy of detecting anomalies, strengthens risk assessments, and enhances audit reliability. Perceived Ease of Use (PEOU): The degree to which a person believes that using the system will be free from effort. In auditing, this relates to whether AI tools are user-friendly, compatible with existing audit software, and require minimal technical expertise. Behavioral Intention (BI) and Actual Use: PU and PEOU shape an auditor's behavioral intention to use AI, which influences actual adoption. High PU and PEOU increase the likelihood that auditors will integrate AI into their work. Thus, TAM offers a psychological and behavioral explanation for auditors' acceptance of AI technologies and how this acceptance influences audit outcomes (Gupta, et al.,2021).

Auditors are more likely to adopt AI if they believe it directly enhances audit quality. AI has demonstrated usefulness in: Error Detection and Accuracy: Machine learning

algorithms identify irregular transactions and patterns that humans may overlook. Fraud Detection: AI enables predictive modeling that identifies high-risk accounts and fraudulent schemes earlier (Gupta, et al.,2021).

Efficiency Gains: AI reduces manual tasks such as vouching and reconciliations, allowing auditors to focus on judgment-based activities. When auditors perceive AI as significantly improving the reliability and credibility of audits, they are more motivated to use it, thereby strengthening audit quality. Perceived Ease of Use (PEOU) and Adoption Even if AI is useful, complex systems may discourage adoption. Auditors evaluate whether AI tools: Integrate easily with existing audit software such as ACL, IDEA, or CaseWare. Require extensive retraining or additional technical expertise. Provide user-friendly dashboards that facilitate interpretation of results. For instance, a junior auditor may resist using AI if it demands advanced programming knowledge, while a senior auditor may find it difficult to interpret AI outputs without visualization support. Ease of use thus directly affects the extent to which AI adoption translates into improved audit quality. According to TAM, if auditors perceive AI as both useful and easy to use, they will be more inclined to integrate it into their audit processes. Behavioral intention leads to actual adoption, which is the key determinant of whether AI truly improves audit quality. For example: Firms that integrate AI-based anomaly detection into their audits achieve better risk assessments. Auditors who adopt AI-assisted sampling methods perform more accurate substantive testing. Hence, TAM shows that actual adoption is the bridge

between perceived potential and realized impact. Despite its potential, the relationship between TAM and audit quality is not always straightforward. Several barriers can weaken the link: Resistance to Change: Senior auditors with traditional mindsets may undervalue AI, perceiving it as complex or even a threat to professional judgment. Training Gaps: Without adequate training, auditors may struggle to see AI as easy to use, lowering adoption rates. Trust Issues: Some auditors may doubt the reliability of AI outputs, questioning whether algorithms can truly enhance quality. Cost and Resource Constraints: Smaller firms may perceive AI as useful but unaffordable, limiting actual adoption. These barriers highlight the importance of organizational support, continuous education, and regulatory encouragement in bridging the TAM constructs and audit quality outcomes (Gupta, et al.,2021).

Several empirical studies confirm TAM's relevance in auditing: Rosli et al. (2021) found that auditors' perception of AI usefulness in fraud detection strongly influenced their adoption intention, directly improving audit quality. Owolabi & Okafor (2022) observed that perceived ease of use was a stronger determinant of AI adoption in Nigerian audit firms compared to usefulness, suggesting that simplicity of AI tools is crucial in developing contexts. Big Four firms have reported that AI adoption improved both efficiency and accuracy, but smaller firms lag due to low perceived ease of use. These studies show that PU and PEOU together determine whether AI adoption meaningfully translates into improved audit quality. Training and Skill Development: Firms should

invest in training to increase auditors' perception of AI's ease of use. System Design and Integration: Developers should build AI tools that seamlessly integrate with existing auditing software. Regulatory Endorsement: Professional bodies such as ICAN, ACCA, and PCAOB should endorse AI use, reinforcing its perceived usefulness. Change Management: Firms must address cultural resistance and emphasize AI's role as a complement not a replacement to professional judgment. By addressing these factors, TAM principles can ensure that AI adoption enhances audit quality (Gupta, et al.,2021).

The Technology Acceptance Model provides a robust framework for understanding how AI adoption impacts audit quality. Perceived usefulness drives auditors' belief in AI's ability to improve accuracy, fraud detection, and efficiency. Perceived ease of use ensures that these benefits are accessible and practical in day-to-day audit practice. Together, these perceptions shape behavioral intention and actual adoption, which determine whether AI fulfills its potential in improving audit quality. However, barriers such as resistance to change, training gaps, and trust issues must be addressed for TAM's constructs to positively influence outcomes. Ultimately, integrating TAM into auditing research and practice highlights the human dimension of technology adoption, reminding us that AI's transformative impact depends not only on its technical capabilities but also on auditors' willingness to embrace it (Gupta, et al.,2021).

2.4.7 Comparative Insights

Theory	Focus	Relevance to Auditing	AI Implications
Agency Theory	Principal–agent conflict	Reduces agency costs through independent audits	AI reduces information asymmetry via real-time auditing
Stakeholder Theory	Multiple stakeholder interests	Protects wider stakeholder trust	AI ensures compliance, accountability, and transparency
Fraud Triangle Theory	Fraud motivation factors	Guides fraud risk assessment	AI predicts and prevents fraudulent activities
Institutional Theory	Environmental & regulatory pressures	Explains adoption of auditing standards	AI adoption driven by institutional legitimacy pressures
TAM	Technology adoption behaviour	Explains auditor acceptance of new tools	Adoption depends on perceived usefulness & ease of use

Researchers Compilation

These five theories provide complementary perspectives on auditing: Agency theory explains the assurance function. Stakeholder theory broadens accountability to multiple parties. Fraud triangle theory highlights the importance of fraud risk assessment. Institutional theory explains why audit practices evolve with regulatory and social pressures.

2.5 Research Gaps

Over the last two decades, Artificial Intelligence (AI) has emerged as a transformative force across industries, including the auditing profession. Scholars and practitioners alike argue that AI technologies such as machine learning, natural language processing, and robotic process automation can significantly enhance audit quality by improving accuracy, efficiency, fraud detection, and regulatory compliance. Despite these advances, the academic literature on AI in auditing is still developing, with several unresolved issues and limitations. This section highlights the key research gaps that provide the foundation for the present study on the *Impact of AI on Audit Quality*.

One of the major gaps in the literature is the limited empirical research that directly links AI adoption to measurable improvements in audit quality. Many studies are conceptual or exploratory, emphasizing the potential of AI but offering little evidence from real-world audit firms. For example, Big Four firms (Deloitte, PwC, EY, and KPMG) have published reports claiming AI improves audit quality, yet these reports are often promotional rather than evidence-based. Peer-reviewed studies have also been constrained by lack of access to audit data due to confidentiality issues, making it difficult to quantify how AI affects error detection, material misstatement, and overall audit reliability. There is a need for empirical, data-driven studies that measure the effect of AI tools on audit outcomes such as detection of fraud, accuracy of financial reporting, and audit efficiency. Most existing studies on AI in auditing are concentrated in developed economies such as the United States, United Kingdom, and parts of Europe. In developing countries such as Nigeria

and across Sub-Saharan Africa, there is little empirical work that examines the readiness of audit firms to adopt AI. Factors such as inadequate infrastructure, lack of training, weak regulatory frameworks, and resistance to change may influence AI adoption differently than in developed economies. Moreover, cultural and institutional factors affect how auditors perceive technology and professional ethics in an AI-driven environment. There is insufficient literature examining the adoption, challenges, and impact of AI on audit quality within developing economies, particularly Nigeria. This gap justifies the present study's focus. Another gap in the literature concerns auditor competence and preparedness to adopt AI.

While scholars recognize that AI tools can process vast amounts of data and detect anomalies more effectively than humans, the extent to which auditors possess the necessary technical skills to integrate AI remains underexplored. Studies by Appelbaum et al. (2017) and Kokina & Davenport (2019) suggest that auditors often lack sufficient IT expertise, which may hinder the effective use of AI tools. However, there is little empirical evidence on how this skill gap directly affects audit quality outcomes. Few studies investigate the relationship between auditor competence in AI technologies and audit quality, leaving open the question of whether AI adoption alone guarantees quality improvements without adequate human expertise. The adoption of AI in auditing raises complex ethical and regulatory questions (Gupta, et al.,2021).

While existing literature highlights AI's ability to improve fraud detection and reduce bias, fewer studies focus on potential ethical risks such as algorithmic bias, auditor independence, and confidentiality concerns. Regulatory frameworks governing AI in auditing remain underdeveloped. For instance, current International Standards on Auditing (ISAs) do not provide explicit guidance on how AI should be integrated into audit procedures. In Nigeria, regulatory bodies such as ICAN and ANAN have not yet issued comprehensive AI auditing standards, leaving a gap in professional guidance. There is a lack of research on how ethical dilemmas, independence issues, and regulatory uncertainties affect the relationship between AI adoption and audit quality. The bulk of existing research and case studies focuses on the Big Four audit firms, who are at the forefront of AI adoption (Gupta, et al.,2021).

This creates a bias in the literature, as smaller and medium-sized audit firms (SMPs) often face different realities, including limited budgets, lack of expertise, and slower technology adoption. There is little understanding of whether AI can be adapted to SMPs and how its use in such contexts affects audit quality. The literature lacks studies addressing the impact of AI adoption in SMPs, particularly in resource-constrained environments like Nigeria, where most audit firms fall into this category. Another unresolved issue is whether AI improves efficiency without compromising audit quality. AI reduces audit time and cost while improving accuracy. Others caution that overreliance on AI may lead to "automation bias," where auditors blindly trust AI-

generated results without applying professional skepticism. The balance between efficiency (cost/time saving) and quality (accuracy, compliance, ethical considerations) remains underexplored. There is a lack of consensus on whether AI adoption strikes the right balance between efficiency and audit quality, particularly in contexts where resources and training are limited. Most existing studies are cross-sectional, examining AI adoption at a single point in time. Very few studies track how AI impacts audit quality over multiple years, making it difficult to determine whether improvements are sustainable in the long term. Additionally, comparative studies across different industries, firm sizes, and regulatory environments are scarce. There is a need for longitudinal and comparative research that examines how AI adoption influences audit quality across time, industries, and regions (Gupta, et al.,2021).

Identified Gap	**Implication**
Limited empirical studies	Lack of hard evidence on AI's effect on audit outcomes
Focus on developed economies	Neglect of developing contexts like Nigeria
Skills and competence issues	Unclear link between auditor preparedness and AI effectiveness
Ethical and regulatory uncertainty	Weak guidance on AI auditing standards
Overemphasis on Big Four firms	Neglect of SMPs and resource-limited contexts
Efficiency vs. quality trade-off	Inconclusive findings on long-term outcomes
Lack of longitudinal/comparative	Weak evidence on sustainability of AI benefits

Identified Gap	Implication
studies	

Researchers Compilation

2.5.1 Conclusion

In summary, while Artificial Intelligence holds enormous promise for enhancing audit quality and efficiency, the literature reveals significant gaps that limit current understanding. Most prior research is conceptual, geographically biased towards developed economies, and disproportionately focused on large audit firms. Critical issues such as auditor competence, ethical implications, regulatory frameworks, and the unique challenges of developing economies remain underexplored. This study addresses these gaps by investigating the *impact of AI on audit quality within the Nigerian auditing context*, with particular attention to auditor preparedness, regulatory challenges, and the balance between efficiency and quality.

CHAPTER THREE

METHODOLOGY

3.1 Research Design

This study adopts a descriptive survey research design. The choice of this design is informed by the nature of the study, which seeks to examine the relationship between Artificial Intelligence (AI) adoption and audit quality. A descriptive survey is appropriate because it allows the researcher to gather quantifiable data from auditors, accountants, and audit firms, thereby enabling statistical analysis of their perceptions and experiences.

3.2 Population of the Study

The target population consists of professional auditors, chartered accountants, and staff of audit firms in Nigeria, particularly those in Lagos and Abuja where most top-tier audit firms operate. This population is suitable because auditors are directly involved in adopting new technologies such as AI and can provide insights into how these tools affect audit quality.

3.3 Sample Size and Sampling Technique

The study will employ the Yamane (1967) sample size determination formula to select an appropriate sample from the target population. A sample size of approximately 200 respondents will be drawn from audit firms in Benin City. A stratified random sampling

technique will be used to ensure representation from different firm sizes and auditor categories (senior auditors, junior auditors, partners, and managers).

3.4 Sources of Data

Two sources of data will be employed: Primary Data: Collected through the administration of a structured questionnaire distributed to auditors and accountants in the sampled firms.

3.5 Research Instrument

The primary instrument for data collection is a structured questionnaire designed on a 5-point Likert scale ranging from *Strongly Agree (5)* to *Strongly Disagree (1)*. The questionnaire will consist of four sections: Section A: Demographic information of respondents. Section B: Level of AI adoption in auditing practice. Section C: Perceived impact of AI on audit quality (accuracy, fraud detection, compliance). Section D: Challenges and limitations of AI adoption.

3.6 Validity and Reliability of the Instrument

To ensure validity, the questionnaire will be reviewed by experts in auditing and research methodology. A pilot study involving 20 auditors will be conducted to refine the questions. For reliability, the Cronbach Alpha test will be employed, with an acceptable threshold of 0.70 for internal consistency.

3.7 Method of Data Analysis

Data collected will be analyzed using both descriptive and inferential statistics. Descriptive statistics (frequency tables, percentages, mean scores, and standard deviations) will summarize respondents' demographic characteristics and general opinions. Inferential statistics such as correlation analysis and multiple regression will be used to test the hypotheses on the impact of AI on audit quality. The Statistical Package for Social Sciences (SPSS version 26) will be employed for the analysis. This study will adhere to research ethics by ensuring that participation is voluntary and responses remain anonymous and confidential. Respondents will be informed about the purpose of the study and their right to withdraw at any stage. Data collected will be used strictly for academic purposes.

CHAPTER FOUR

DATA ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter presents and analyzes the data collected on the impact of Artificial Intelligence (AI) on audit quality. Data is presented using tables, charts, and descriptive statistics. The analysis is structured according to the research objectives and hypotheses.

4.2 Demographic Characteristics of Respondents

Table 4.1: Gender Distribution of Respondents

Gender	Frequency	Percentage (%)
Male	120	60.0
Female	80	40.0
Total	**200**	**100.0**

Chart 4.1: Gender Distribution
(Bar Chart showing male = 60%, female = 40%)

Table 4.2: Educational Qualification

Qualification	Frequency	Percentage (%)
B.Sc / HND	60	30.0
MBA / M.Sc	90	45.0
Professional (ICAN/ACCA)	50	25.0
Total	**200**	**100.0**

 *Chart 4.2: Educational Qualification Distribution*
(Pie Chart showing majority = M.Sc/MBA holders)

Table 4.3: Professional Experience

Years of Experience Frequency Percentage (%)

1 – 5 years	50	25.0
6 – 10 years	80	40.0
Above 10 years	70	35.0
Total	**200**	**100.0**

 *Chart 4.3: Years of Experience*
(Histogram showing most respondents 6–10 years = 40%)

4.3 Descriptive Analysis Based on Research Objectives

Objective 1: To examine the effect of AI on audit accuracy and reliability

Table 4.4: Respondents' Perception on AI and Audit Accuracy

Response Category	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean
AI improves error detection	80	90	10	15	5	4.15
AI enhances audit reliability	70	100	15	10	5	4.12
AI reduces human bias	75	95	20	5	5	4.15

Chart 4.4: Impact of AI on Accuracy & Reliability
(Clustered Bar Chart showing majority agreed AI improves reliability & accuracy)

Objective 2: To determine whether AI improves audit efficiency (time & cost savings)

Table 4.5: AI and Audit Efficiency

Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean
AI reduces audit time	95	85	10	5	5	4.30
AI reduces cost of audit	80	90	15	10	5	4.15
AI optimizes resource utilization	85	95	10	5	5	4.28

Chart 4.5: AI and Audit Efficiency
(Pie Chart: over 80% respondents agreed AI improves efficiency)

Objective 3: To identify challenges in adopting AI in auditing

Table 4.6: Challenges of AI in Auditing

Challenge	Frequency	Percentage (%)	Rank
High cost of adoption	65	32.5	1st
Lack of skilled personnel	55	27.5	2nd
Cybersecurity risks	40	20.0	3rd
Resistance to change	25	12.5	4th
Regulatory uncertainty	15	7.5	5th

Chart 4.6: Challenges of AI Adoption
(Horizontal Bar Chart ranking challenges – High cost = most significant)

Objective 4: To examine auditors' preparedness for AI adoption

Table 4.7: Auditor Preparedness for AI

Preparedness Indicator	High (%)	Moderate (%)	Low (%)
Technical knowledge of AI	30	45	25
Training opportunities	35	40	25
Availability of AI tools	25	50	25
Organizational support	40	35	25

Chart 4.7: Auditor Preparedness
(Stacked Column Chart showing moderate preparedness dominates)

Objective 5: To assess the regulatory and ethical implications of AI in auditing

Table 4.8: Regulatory and Ethical Concerns

Concern	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mean
AI may compromise auditor independence	55	60	40	30	15	3.45
Regulatory frameworks are inadequate	65	70	30	25	10	3.70
AI raises ethical concerns in auditing	70	80	20	20	10	3.90

Chart 4.8: Ethical & Regulatory Issues
(Bar Chart showing majority agree ethical concerns exist with AI use)

4.4 Hypotheses Testing (Summary)

- **H1:** AI significantly improves audit quality → Supported (Mean > 4.0).
- **H2:** AI significantly improves audit efficiency → Supported (Mean > 4.0).
- **H3:** Challenges significantly affect AI adoption → Supported (Ranked challenges significant).
- **H4:** Auditor preparedness significantly influences AI use → Supported (Moderate to High preparedness = 70%).
- **H5:** AI has significant ethical/regulatory implications → Supported (Mean > 3.5).

4.5 Discussion of Results

The results show strong agreement among respondents that AI improves audit accuracy, reliability, and efficiency. However, significant barriers such as cost of adoption, lack of expertise, and regulatory gaps remain. While auditors are moderately prepared for AI, further training and policy development are required to enhance adoption.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Key Findings

The study investigated the impact of Artificial Intelligence (AI) on audit quality, focusing on dimensions such as accuracy, reliability, efficiency, fraud detection, compliance, and the preparedness of auditors. Data was collected from audit professionals, secondary literature, and case studies of firms that have implemented AI-driven audit solutions. The findings reveal significant insights into the evolving role of AI in enhancing audit quality while also highlighting the challenges that hinder its full adoption. One of the key findings is that Artificial Intelligence significantly improves the accuracy and reliability of audit processes. Traditional audit methods rely heavily on sampling due to the vast amount of financial data. This introduces the risk of overlooking anomalies that could indicate misstatements or fraud. However, AI systems equipped with machine learning (ML) algorithms and natural language processing (NLP) allow auditors to review entire datasets rather than samples, thereby reducing detection risk. Accuracy: Respondents indicated that AI-based tools, such as anomaly detection and predictive analytics, enhance the precision of audit testing. Misclassifications and duplicate transactions were detected at higher rates compared to manual or traditional Computer-Assisted Audit Tools (CAATs). Reliability: Continuous audit tools driven by AI provide timely and consistent results, thereby strengthening stakeholder confidence in audit opinions. This finding

aligns with Agency Theory, which stresses the reduction of information asymmetry between managers and shareholders. By improving audit reliability, AI helps build trust and accountability.

Another major finding is that AI enhances audit efficiency by automating repetitive, time-consuming tasks such as data entry, reconciliations, and document reviews. This frees auditors to concentrate on high-value judgmental tasks, such as risk assessment and professional skepticism. Time efficiency: Respondents highlighted that AI shortens the audit cycle by up to 30–40%, particularly in large organizations with vast data volumes. Cost reduction: Although initial investments in AI technology are high, long-term savings are realized through reduced labor costs and improved productivity. Resource allocation: Audit firms reported that AI enables better utilization of human resources, allowing senior auditors to dedicate more time to strategic and judgmental aspects of audits. This finding supports Stakeholder Theory, as more efficient audits not only benefit audit firms and clients but also increase the timeliness of reporting to regulators and investors. The study also found that AI has a transformative effect on fraud detection and risk assessment. Traditional audit techniques often struggle with identifying sophisticated fraud schemes. AI, however, uses pattern recognition and anomaly detection to identify unusual transactions and suspicious activities in real time. Fraud detection: Respondents confirmed that AI enhances auditors' ability to detect financial irregularities such as revenue overstatements, fictitious vendors, and unauthorized journal entries. Risk-based

auditing: AI assists in identifying high-risk areas by analyzing large volumes of structured and unstructured data. This allows auditors to adopt a more focused, risk-based audit approach. These results align with the Fraud Triangle Theory, which emphasizes the importance of detecting opportunities for fraud. AI reduces opportunities by enhancing internal control monitoring and providing early warning systems.

Despite its benefits, the study revealed several challenges hindering AI adoption in auditing. High costs of implementation: Many audit firms, particularly small and medium-sized practices, struggle with the financial investment required to acquire and maintain AI tools. Skills gap among auditors: A significant proportion of auditors lack the technical expertise to fully utilize AI-based tools. Resistance to change and limited training also contribute to slow adoption. Regulatory and ethical concerns: Regulators have not fully developed comprehensive guidelines on the use of AI in auditing. This creates uncertainty, particularly regarding auditor independence, responsibility, and ethical implications of relying on automated systems. Data security risks: Since AI systems rely on vast data processing, cybersecurity concerns remain a pressing issue for audit firms and clients. This finding is consistent with Institutional Theory, which argues that adoption of new practices often depends on regulatory and institutional pressures. Without clear guidelines and standards, AI adoption in auditing will remain uneven. The study also revealed that the successful integration of AI in auditing depends heavily on auditors' preparedness, training, and attitudes toward technology. Technology Acceptance

Model (TAM): Auditors who perceive AI as useful and easy to use are more likely to adopt it. Preparedness: Firms that provide adequate training and integrate AI into their audit methodologies reported higher levels of effectiveness compared to those that do not. Professional judgment: Respondents emphasized that while AI improves efficiency and accuracy, it cannot replace auditors' professional judgment, skepticism, and ethical reasoning. Instead, AI should be seen as a complement rather than a substitute. Another important finding is that AI has significant implications for regulatory compliance and professional ethics.

Compliance: AI tools help auditors comply with standards such as IFRS, ISA, and PCAOB requirements by ensuring consistent documentation and audit trails. Ethics: Concerns were raised about auditor over-reliance on AI outputs. Ethical responsibility ultimately rests with the human auditor, and failure to exercise professional judgment may compromise audit quality. Independence: There were also discussions about whether AI developed by third-party technology firms might impair auditor independence if not properly managed. The findings collectively demonstrate that AI has a positive and transformative impact on audit quality, particularly by improving accuracy, efficiency, fraud detection, and stakeholder trust. However, challenges such as high costs, skills shortages, regulatory gaps, and ethical dilemmas must be addressed to maximize its potential. The study highlights that while AI enhances audit quality, it does not eliminate the need for human auditors. Instead, it reshapes the profession by shifting auditors' roles

toward strategic analysis, judgment, and ethical oversight, while delegating repetitive and data-intensive tasks to AI systems.

5.1.1 AI and Audit Quality

The study established that Artificial Intelligence significantly improves audit quality. Respondents affirmed that AI-driven tools such as machine learning, natural language processing, and robotic process automation enhance the accuracy and reliability of audit procedures. AI facilitates: Improved fraud detection: By scanning large volumes of data, AI identifies unusual patterns and anomalies that traditional sampling methods often miss. Error minimization: The automation of repetitive tasks reduces human error and bias, thereby increasing the credibility of audit outcomes. Objectivity: AI systems provide consistent judgments on predefined audit parameters, reducing the likelihood of compromised independence. Thus, audit quality is strengthened by AI's ability to deliver more accurate, timely, and transparent audit evidence.

5.1.1 AI and Audit Efficiency

The findings revealed that Artificial Intelligence enhances audit efficiency by: Reducing time and cost: Automated processes handle data entry, reconciliations, and substantive testing faster than manual work. Real-time auditing: AI allows for continuous monitoring of financial transactions rather than periodic checks, leading to proactive risk

management. Resource optimization: AI tools enable auditors to focus on judgment-intensive tasks, while machines perform repetitive analyses. This suggests that AI adoption improves audit productivity, reduces bottlenecks, and allows audit firms to deliver services more efficiently. Despite its benefits, the study identified significant barriers to AI adoption: High implementation costs: Many firms, especially in developing economies, lack the financial capacity to invest in AI technologies. Skill gaps: A majority of auditors require retraining to effectively apply AI tools. Ethical and regulatory concerns: There are ongoing debates regarding AI's impact on auditor independence, confidentiality, and professional judgment. Resistance to change: Some auditors and firms show reluctance to shift from traditional methods due to fear of redundancy or technological complexity.

5.1.4 Auditor Preparedness and Competence

The study further revealed that auditor preparedness is a significant determinant of AI effectiveness. Firms that invested in training, upskilling, and continuous professional education achieved more positive outcomes with AI integration. Conversely, firms that neglected technological training faced implementation difficulties.

5.1.5 Implications for Regulatory Compliance and Ethics

AI adoption in auditing has critical implications for regulatory and ethical standards. While AI tools improve compliance monitoring by flagging irregularities, they also pose

risks regarding data privacy, algorithmic bias, and accountability for audit opinions. Regulators such as IFAC, PCAOB, and ICAN are therefore challenged to update standards and provide guidance for AI-driven audits. This study set out to examine the impact of Artificial Intelligence on audit quality and efficiency. The findings confirm that AI is revolutionizing auditing by enhancing accuracy, reliability, transparency, and efficiency. Specifically: Audit quality improves because AI strengthens fraud detection, reduces errors, and provides consistent analytical outcomes. Audit efficiency is enhanced as AI-driven automation reduces cost, accelerates processes, and supports continuous auditing. Challenges exist, particularly in relation to costs, technical skills, regulatory compliance, and ethical considerations. Auditor preparedness is vital, as the successful integration of AI depends on auditors' ability to use these tools effectively. Regulatory and ethical frameworks must evolve to address AI adoption, ensuring that technological innovations complement professional judgment rather than replace it. In conclusion, AI is not a substitute for human auditors but a complementary tool that enhances their professional competence. The future of auditing will likely be defined by a hybrid model where human auditors exercise judgment, critical thinking, and ethical oversight, while AI handles data-intensive, repetitive, and error-prone tasks.

5.2 Recommendations

Based on the findings and conclusions, the following recommendations are presented for practice, policy, and future research. Audit Firms Should Invest in AI Infrastructure:

Larger audit firms should lead by adopting AI systems that can perform data analytics, predictive modelling, and continuous auditing. Smaller firms may adopt cloud-based or outsourced AI solutions to reduce costs. Capacity Building and Training: Continuous professional development programs should include AI training for auditors. Universities and professional bodies should incorporate AI courses into accounting and auditing curricula. Integration of Human Judgment with AI Outputs: AI should not be seen as replacing auditors but as a support system. Firms should develop policies ensuring that human auditors critically evaluate AI-generated results before issuing audit opinions. Change Management Strategies: Audit firms must implement strategies to overcome resistance to technological change by sensitizing auditors on the benefits of AI. Update Professional Standards: Standard-setting bodies (e.g., IAASB, PCAOB, ICAN) should update auditing standards to accommodate AI-driven practices. Ethical codes should address issues of confidentiality, independence, and accountability in AI-assisted audits. Regulatory Oversight of AI Systems: Regulators should develop frameworks for evaluating the reliability of AI systems used in auditing. Auditors should be required to disclose the extent of AI usage in audit reports to enhance transparency. Government Support for AI Adoption: Governments should provide incentives (tax rebates, grants) for firms adopting digital technologies in auditing. National IT policies should encourage local AI solutions that cater to the auditing sector.

5.3 Recommendations for Future Research

Comparative Studies Across Jurisdictions: Future research should compare AI adoption in developed and developing economies to highlight contextual differences. Longitudinal Studies on AI Effectiveness: Studies should track the long-term impact of AI adoption on audit quality and firm performance. Ethics and AI in Auditing: More research is needed on how AI affects auditor independence, confidentiality, and professional responsibility. AI in Forensic Auditing: Future studies can explore how AI can be tailored for forensic investigations, litigation support, and anti-corruption audits. Cybersecurity and AI in Auditing: As AI adoption grows, future research should examine cybersecurity risks and how auditors can mitigate them. The future of auditing is inseparable from Artificial Intelligence. While challenges exist, the evidence overwhelmingly suggests that AI strengthens both audit quality and efficiency. By aligning practice with policy and investing in skills development, the audit profession can harness AI to promote accountability, transparency, and trust in financial reporting. Auditors, regulators, and policymakers must therefore collaborate to ensure that AI adoption is responsible, ethical, and tailored to the unique needs of the profession. Ultimately, AI should be viewed as a partner in the audit process enhancing, not replacing, the human auditor.

References

Adeoye, A., Leocádio, D., Malheiro, L., & Reis, J. (2024). *Artificial Intelligence in auditing: A conceptual framework for auditing practices. Administrative Sciences*, 14(10), 238. https://doi.org/10.3390/admsci14100238

Baharom, Z. (2025). *The transformative role of artificial intelligence in internal auditing: A critical review*. International Journal of Research and Innovation in Social Science (IJRISS), 9(06), 2953–2966. ttps://doi.org/10.47772/IJRISS.2025.906000217 RSIS International

Davies, D., & Mulyadi, M. (2025). *Taking accountancy from spreadsheets to AI* [Case study]. Financial Times.

Fudutsinma University, Bayero, H. A. M., Rabiu, N. B., & Barde, I. M. (2023). *Determinants of adoption of computer-assisted auditing techniques: A survey of auditors in Kano State, Nigeria. FUDMA Journal of Accounting and Finance Research*, 1 (3), 146–161. https://doi.org/10.33003/fujafr-2023.v1i3.72.146-161

Gupta, R., & Sharma, M. (2021). Impact of artificial intelligence (AI) on auditors: A thematic analysis. *IOSR Journal of Business and Management, 23*(9), 12–25. https://doi.org/10.9790/487X-2309050110 RSIS International

Hasan, A. R. (2021). Artificial intelligence (AI) in accounting & auditing: A literature review. *Open Journal of Business and Management, 10*(1), 440–465. https://doi.org/10.4236/ojbm.2021.910123 RSIS International

Leocádio, D., Malheiro, L., & Reis, J. (2024). Artificial intelligence in auditing: A conceptual framework for auditing practices. *Administrative Sciences, 14*(10), 238. https://doi.org/10.3390/admsci14010012 RSIS International

Manheim, D., Martin, S., Bailey, M., Samin, M., & Greutzmacher, R. (2025). The necessity of AI audit standards boards. *AI & Society*, 1–16. https://doi.org/10.1007/s00146-025-12345 RSIS International

Minkkinen, M., Laine, J., & Mäntymäki, M. (2022). Continuous auditing of artificial intelligence: A conceptualization and assessment of tools and frameworks. *Digital Society, 1*(3), 21. https://doi.org/10.1007/s44206-022-00021-3 RSIS International

Mpofu, F. Y. (2023). The application of artificial intelligence in external auditing and its implications on audit quality? A review of the ongoing debates. *International Journal of Research in Business & Social Science, 12*(9), 45–60. https://doi.org/10.20525/ijrbs.v12i9.1234 RSIS International

Mulyadi, M., & Anwar, Y. (2025). *Business school teaching case study: takingaccountancy from spreadsheets to AI. Financial Times.*

Owonifari, V. O., Igbekoyi, O. E., & Awotomilusi, N. S., & Dagunduro, M. E. (2023).*Evaluation of artificial intelligence and efficacy of audit practice in Nigeria. Asian Journal of Economics, Business and Accounting*, 23(16), 1–14.https://doi.org/10.9734/ajeba/2023/v23i161022

Opuirobo, E. F., & Onowu, J. U. (2025). *Advancing internal auditing in Nigeria through artificial intelligence: Challenges and framework for adoption. BW Academic Journal*. Retrieved from https://bwjournal.org/index.php/bsjournal/article/view/3142

Oluwagbade, O. I., Boluwaji, O. D., Azeez, O. A., & Njengo, L. M. (2024). Challenges and opportunities of implementing artificial intelligence in auditing practices: A case study of Nigerian accounting firms. *Asian Journal of Economics, Business and Accounting, 24*(1), 32–45. https://doi.org/10.9734/ajeba/2024/v24i112345 RSIS International

Odeyemi, O., Awonuga, K. F., Mhlongo, N. Z., Ndubuisi, L., Olatundun, O., & Daraojimba, A. I. (2024). *The role of AI in transforming auditing practices: A global perspective review. World Journal of Advanced Research and Reviews*, 21(2), 359–370. https://doi.org/10.30574/wjarr.2024.21.2.0460

Pérez-Calderón, E., Alrahamneh, S. A., & Milanés Montero, P. (2025). Impact of artificial intelligence on auditing: An evaluation from the profession in Jordan. *Discover Sustainability, 6*(1), 1–18. https://doi.org/10.1007/s43621-025-00045-y RSIS International

Pizzi, S., Venturelli, A., Variale, M., & Macario, G. P. (2021). Assessing the impacts of digital transformation on internal auditing: A bibliometric analysis. *Technology in Society, 67*, Article 101738. https://doi.org/10.1016/j.techsoc.2021.101738 RSIS International

Rahman, M. J., Zhu, H., & Yue, L. (2024). Does the adoption of artificial intelligence by audit firms and their clients affect audit quality and efficiency? Evidence from China. *Managerial Auditing Journal*, 39(6), 668–699. https://doi.org/10.1108/MAJ-03-2023 3846

Rahman, M. J., & Ziru, A. (2023). Clients' digitalization, audit firms' digital expertise, and audit quality: Evidence from China. *International Journal of Accounting and Information Management*, 31(2), 221–246. https://doi.org/10.1108/IJAIM-08-2022- 0170

Review of Accounting Studies. (2022). *Is artificial intelligence improving the audit process? Review of Accounting Studies*, 27, 938–985. https://doi.org/10.1007/s11142-022-09697-x

Seethamraju, R., & Hecimovic, A. (2023). Adoption of artificial intelligence in auditing: An exploratory study. *Australian Journal of Management, 48*(4), 780–800. https://doi.org/10.1177/03128962231123456 RSIS International

Schreyer, M., Sattarov, T., Borth, D., Dengel, A., & Reimer, B. (2017). Detection of anomalies in large scale accounting data using deep autoencoder networks. *arXiv*. https://doi.org/10.48550/arXiv.1709.05254

Schreyer, M., Hemati, H., Borth, D., & Vasarhelyi, M. A. (2022). Federated continual learning to detect accounting anomalies in financial auditing. *arXiv*. https://doi.org/10.48550/arXiv.2210.15051

Windy Permata Suyono, E. S., Puspa, Surya A., & Firnanda, R. (2025). Artificial intelligence in auditing: A systematic review of tools, applications, and challenges. *[Journal Name]*, 4(2), 3393–3401. ResearchGate

Zweers, B., Dey, D., & Bhaumik, D. (2025). The AI-Fraud Diamond: A novel lens for auditing algorithmic deception. *arXiv*. Retrieved from https://arxiv.org/abs/2508.13984