THE IMPACT OF ARTIFICIAL INTELLIGENCE ON AUDIT EFFICIENCY

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

APRIL,2025

DECLARATION

I, **Ebowe Osamudiamen** declare that:

I. This project is based on a study undertaken in the Department of Accounting, University of Benin under the supervision of **Prof A.S Omoye**.

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

III. All ideas and view are products of my personal research and that of my supervisor and where the views of others have been expressed, they have been duly acknowledged.

______________________________ ____________________

Ehijele David AIGBOKHAEBHOLO **Date**

CERTIFICATION

We certified that this work was carried out Ebowe Osamudiamen with the matriculation number MGS2010850 in the Department of Accounting, University of Benin, Benin City.

Prof A.S Omoye **Date**

Project Supervisor

Dr G. O IKHU-OMOREGBE **Date**

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Head of Department

DEDICATION

This research work is dedicated to God Almighty who is too faithful to fail me, for his unwavering mercies, unconditional love, strength which kept me going all through my academic pursuit in this university.

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TABLE OF CONTENTS

LIST OF TABLES

ABSTRACT

This study examines the impact of artificial intelligence (AI) technologies on audit efficiency, with a specific focus on selected professional organizations in Benin City, Nigeria. Employing a survey research design, the study gathered data from 50 respondents across various industries using structured questionnaires. The analysis utilized both correlation and linear regression techniques to assess the relationship between AI components—Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics—and audit efficiency.

The findings reveal that Machine Learning and Predictive Analytics significantly enhance audit efficiency, as evidenced by their strong positive correlations and statistically significant regression coefficients. These technologies contribute to improved financial reporting accuracy, enhanced fraud detection, and reduced audit risks. Conversely, NLP and RPA did not show statistically significant effects, suggesting that their integration into audit workflows may be limited or at a developmental stage.

The study underscores the transformative potential of data-driven technologies in modern auditing, advocating for strategic investments in advanced analytics. It also highlights the need for further research to understand the contextual factors influencing the effectiveness of AI tools, particularly NLP and RPA, within different organizational and industry settings. The results provide a valuable framework for policymakers, audit professionals, and corporate leaders aiming to leverage AI for more efficient, accurate, and predictive audit functions.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

The emergence of artificial intelligence (AI) is fundamentally transforming various sectors globally, and the field of auditing is no exception. Auditors are increasingly leveraging AI to enhance audit efficiency by streamlining processes, automating routine tasks, and improving the accuracy of risk assessment. AI's capabilities in data analytics and anomaly detection allow auditors to process large volumes of data with greater precision, thereby reducing human error and increasing the reliability of audit findings (Gartner, 2019). Consequently, AI's integration into auditing practices is not merely a technological advancement but represents a paradigm shift in how audit efficiency is conceptualized and achieved.

In Nigeria, the adoption of AI in audit processes remains in the nascent stages but is gaining traction due to increased awareness of its potential benefits (Owonifari, Igbekoyi, Awotomilusi, & Dagunduro, 2023). Financial institutions, regulatory bodies, and auditing firms recognize that traditional audit methods are often constrained by manual processes that can be time-consuming and resource-intensive (Dagunduro, Falana, Adewara, & Busayo, 2023). AI-driven tools, such as machine learning algorithms, can analyze patterns in financial data, highlight anomalies, and flag potential fraud, providing auditors with enhanced insights into financial transactions. This shift is particularly pertinent given Nigeria's high incidence of corporate fraud, where approximately 54% of businesses reported fraud cases in recent years (PwC, 2019).

The Nigerian auditing landscape is further influenced by socio-economic factors, including regulatory challenges and limited access to cutting-edge technology. Local audit firms often face barriers in adopting advanced AI tools due to high costs and a shortage of skilled personnel. Nonetheless, as global trends continue to influence the Nigerian market, auditors in Nigeria are progressively exploring AI solutions as a strategic investment for improving audit efficiency. Research suggests that AI could reduce audit time by up to 50%, thus freeing up auditors to focus on more complex, judgment-intensive tasks (Deloitte, 2020). This efficiency gain could be particularly advantageous in Nigeria, where economic pressures demand that businesses operate more cost-effectively while maintaining compliance with regulatory standards.

The impact Artificial intelligence has on audit efficiency has gone beyond operational improvements to include enhanced compliance with international financial reporting standards (IFRS). For instance, the Central Bank of Nigeria (CBN) has advocated for technological integration to support regulatory compliance and ensure transparency in financial reporting (CBN, 2018). By automating data-intensive tasks, AI facilitates compliance with these standards, reducing the risk of regulatory breaches and fostering investor confidence in Nigerian markets.

Despite these benefits, the adoption of AI in auditing also presents certain challenges. Ethical concerns, data privacy issues, and the need for continuous upskilling of auditors are significant considerations. Addressing these challenges is essential for maximizing the potential of AI in auditing while ensuring that it aligns with Nigeria's regulatory and ethical standards.

AI influence on audit efficiency is multifaceted, it encompassing both opportunities for enhanced accuracy and speed and challenges related to ethical and regulatory compliance. Understanding these dynamics is essential for Nigerian firms as they navigate the evolving landscape of AI-driven auditing. This study aims to examine the specific impacts of AI on audit efficiency in Nigeria, exploring both the benefits and the limitations within the Nigerian auditing context.

1.2 Statement of Problem

In an ideal scenario, audit firms in Nigeria would fully utilize Artificial Intelligence (AI) to enhance audit efficiency, enabling auditors to process large data sets rapidly, identify irregularities, and generate reliable financial insights. Such integration would allow auditors to detect fraud more accurately, streamline compliance with regulatory standards, and improve the overall quality of financial reporting (Deloitte, 2020). Auditors could use AI-driven tools, such as machine learning algorithms and predictive analytics, to enhance their analytical capabilities and make data-driven decisions, thereby strengthening Nigeria's financial landscape and building investor confidence (KPMG, 2019).

Currently, however, the integration of AI in Nigerian audit practices faces significant challenges. Despite the potential benefits, adoption remains limited due to barriers such as high implementation costs, a lack of skilled AI professionals, and data privacy concerns (PwC, 2019). Many Nigerian firms, particularly small to medium-sized enterprises, struggle to afford advanced AI systems due to economic constraints, and a shortage of expertise in AI implementation hampers the effectiveness of existing tools (Central Bank of Nigeria, 2020). Moreover, regulatory frameworks in Nigeria have not yet fully addressed the ethical and operational implications of AI in auditing, leaving auditors uncertain about compliance expectations and data security requirements (Financial Reporting Council of Nigeria, 2019). As a result, audit firms often rely on traditional, manual methods that are time-consuming and prone to human error, which diminishes the potential efficiency gains AI could offer.

If these challenges remain unaddressed, Nigerian audit firms risk lagging behind global standards in audit efficiency, potentially undermining the credibility and transparency of financial reports. Without adopting AI, auditors may continue to face increased workloads and diminished capacity to conduct thorough audits, which could lead to undetected fraud, financial misstatements, and a loss of public trust (EY, 2018). Furthermore, inadequate regulatory guidance may lead to ethical and legal complications, as the use of AI without robust oversight could compromise data privacy and amplify biases in decision-making processes (OECD, 2019).

This research is essential to understanding how AI can be effectively integrated into the Nigerian auditing industry to enhance audit efficiency while navigating the unique socio-economic and regulatory landscape of Nigeria. By examining the barriers to AI adoption and exploring potential solutions, this study aims to contribute to the development of an audit framework that leverages AI for increased efficiency, accuracy, and compliance, thereby promoting transparency and trust in Nigeria's financial sector.

1.3 Research Objectives

The primary objective is to study the impact of Artificial intelligence on Audit efficiency while the specific objectives are;

1. To examine the impact of Machine Learning on audit efficiency.
2. To assess the effect of Natural Language Processing (NLP) on audit efficiency.
3. To evaluate the role of Robotic Process Automation (RPA) in enhancing audit efficiency.
4. To investigate the influence of Predictive Analytics on audit efficiency.

1.4 Research Questions

The following question were formulated to guide this research

1. What is the impact of Machine Learning on audit efficiency?
2. How does Natural Language Processing (NLP) affect audit efficiency?
3. What role does Robotic Process Automation (RPA) play in enhancing audit efficiency?
4. What influence does Predictive Analytics have on audit efficiency?

1.5 Research Hypothesis

The following hypotheses guiding this research were stated in the null form

1. Machine Learning has no significant positive impact on audit efficiency.
2. Natural Language Processing (NLP) has no significantly affects on audit efficiency.
3. Robotic Process Automation (RPA) has played no significant role in enhancing audit efficiency.
4. Predictive Analytics has no significant influence on audit efficiency.

1.6 Scope of Study

This study primarily aims to examine the effects of Artificial Intelligence (AI) on audit efficiency, with a specific focus on audit firms in Benin City. It explores AI applications such as Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics, which are increasingly adopted in auditing to enhance accuracy, speed, and overall efficiency.

The study reviews 19 firms registered with the Institute of Chartered Accountants of Nigeria (ICAN), including accounting firms, corporate finance departments, and public service organizations. These firms were selected because they are actively engaged in audit practices within Benin City, making them suitable for this research.

The choice of Benin City is based on its strategic importance as an academic and commercial hub in Edo State, as well as its proximity to the University of Benin. This location facilitates access to relevant data and resources, ensuring the feasibility of the study.

1.7 Significance of the Study

The integration of Artificial Intelligence (AI) into auditing has the potential to enhance efficiency, accuracy, and reliability. This study examines the impact of AI technologies—Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics on audit efficiency, addressing growing concerns in Nigeria's financial sector regarding transparency, fraud detection, and data-driven insights.

The research is relevant to audit firms and professionals, demonstrating how AI can streamline audits, reduce labor, and improve financial reporting. It also provides insights for regulatory bodies like the Financial Reporting Council of Nigeria (FRCN) and the Central Bank of Nigeria (CBN) on integrating AI within national compliance standards.

Businesses across Nigeria can benefit from AI-driven audit efficiency, as it enhances financial reliability, strengthens investor trust, and supports economic growth. Additionally, this study contributes to academic and professional knowledge on AI in auditing, particularly in Africa, where research remains limited. It highlights the infrastructural, regulatory, and educational frameworks needed to support AI adoption, making it valuable to practitioners, policymakers, and researchers.

CHAPTER TWO

LITERATURE REVIEW

2.1 Conceptual Framework

The conceptual framework provides the foundation for understanding the interplay between Artificial Intelligence (AI) and audit efficiency in the context of the auditing process. It outlines the key concepts, variables, and relationships that guide this study. In recent years, AI has revolutionized the auditing profession, enabling automation, enhanced data analytics, and improved decision-making processes. These advancements have the potential to transform traditional audit practices by increasing accuracy, reducing errors, and saving time.

This section aims to establish a clear understanding of the core concepts and their interconnections, which are critical for addressing the study's objectives

2.1.1 Artificial Intelligence

The history of Artificial Intelligence (AI) spans decades, marked by innovations and milestones that have transformed the field into a cornerstone of modern technology. AI's origins trace back to the 1950s when the term "artificial intelligence" was first coined at the Dartmouth Conference in 1956. During this conference, researchers envisioned a future where machines could replicate human intelligence by performing tasks such as reasoning, learning, and decision-making (Russell & Norvig, 2021).

The early stages of AI focused on symbolic reasoning, with researchers developing programs capable of solving mathematical problems and playing games. Notable breakthroughs included the Logic Theorist (1956), considered the first AI program, and the General Problem Solver (GPS) in 1959. These systems demonstrated the potential of rule-based problem-solving but were limited by computational power and data availability (McCarthy, 2007).

The enthusiasm of the early years was followed by periods known as AI winters, characterized by reduced funding and interest due to unmet expectations. However, the field experienced a resurgence in the 1980s with the advent of expert systems, which used domain-specific knowledge to perform tasks like medical diagnosis. Despite initial success, the high cost of development and maintenance led to another decline in AI interest by the late 1980s (Müller, 2016).

The modern era of AI began in the 2000s, fueled by advances In computing power, data availability, and algorithms. Key developments included deep learning, a subset of machine learning that uses neural networks to analyze large datasets. This approach enabled breakthroughs in image recognition, natural language processing (NLP), and robotics. For instance, the development of systems like IBM Watson, capable of understanding and processing unstructured data, highlighted AI's applicability in diverse fields such as healthcare, finance, and autonomous vehicles (Hao, 2020; IEEE, 2024). Recent advancements have also focused on ethical AI and robust systems. Researchers emphasize explainability, fairness, and accountability to ensure AI systems align with societal values and can be trusted for high-stakes applications (MIT Lincoln Laboratory, 2024).

Today, AI is seen as a transformative force across industries, revolutionizing how tasks are performed and decisions are made. The integration of AI into everyday life, from virtual assistants to predictive analytics, reflects its growing influence. However, challenges remain, particularly concerning general AI, which aims to achieve human-like cognition. While narrow AI dominates current applications, the pursuit of general AI continues to drive research efforts globally (IEEE, 2024).

2.1.2 The Auditing Landscape

Auditing, as a systematic examination of financial records, has its roots in ancient civilizations where trade and taxation necessitated accountability. Historical evidence suggests that auditing practices were employed in ancient Mesopotamia, Egypt, and Greece to ensure accuracy in tax collection and the management of public resources (Ramamoorti, 2016). These early audits were rudimentary, relying on manual verification and cross-checking of records by appointed officials.

The term “audit” derives from the Latin word audire, meaning “to hear,” reflecting early practices where auditors verbally confirmed the accuracy of accounts. During the Roman Empire, auditing played a critical role in overseeing the finances of large estates and public funds, demonstrating its importance in governance and accountability (Lee & Azham, 2018).

The Industrial Revolution of the 18th and 19th centuries marked a significant evolution in auditing practices. The rise of large-scale businesses, joint-stock companies, and the separation of ownership from management created a pressing need for independent verification of financial information. This era saw the emergence of formalized auditing practices, driven by the demand for transparency among shareholders and creditors (Matthews, 2020). In the late 19^{th} century, professional accounting and auditing bodies, such as the Institute of Chartered Accountants in England and Wales (ICAEW), were established to standardize practices and uphold ethical standards.

The 20th century ushered in significant transformations in auditing due to advancements in technology, the globalization of businesses, and the complexity of financial transactions. The adoption of computerized systems in the 1960s and 1970s revolutionized auditing by automating routine tasks, enabling auditors to focus on analytical and risk-based approaches. The introduction of International Standards on Auditing (ISAs) by the International Federation of Accountants (IFAC) in 1977 further harmonized global practices, ensuring consistency and reliability in audit engagements across borders (Knechel, 2016).

In the contemporary era, auditing has evolved into a multidisciplinary field encompassing financial, operational, and compliance audits. Globally, the profession has embraced advanced technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Blockchain, enhancing the accuracy and efficiency of audits. These tools enable real-time analysis of large datasets, improving fraud detection and risk assessment capabilities (Zhou et al., 2021). Additionally, the rise of environmental, social, and governance (ESG) reporting has expanded the scope of audits to include sustainability and ethical considerations, reflecting broader societal expectations.

Auditing remains a cornerstone of corporate governance and financial accountability worldwide. While challenges such as regulatory changes, cybersecurity risks, and ethical dilemmas persist, the field continues to adapt and innovate to maintain its relevance and effectiveness in an increasingly complex global economy.

2.1.3 Auditing in Nigeria

Auditing practices in Nigeria traces its roots back to the colonial era when British accounting practices were introduced into the country. Initially, auditing focused on financial accountability for British trading firms and colonial government activities. These early audits were limited in scope, addressing primarily financial compliance and procedural accountability under British laws and standards. By the mid-20th century, the establishment of indigenous firms and the creation of the Institute of Chartered Accountants of Nigeria (ICAN) in 1965 marked a significant shift towards localization of the profession. ICAN, operating under parliamentary authority, set the stage for structured auditing practices and professional development in the country. Alongside ICAN, the Association of National Accountants of Nigeria (ANAN), established in 1979, expanded professional standards by offering alternative certification and training pathways for accountants and auditors.

Fast forward to the present, Nigeria's auditing landscape has evolved into a more sophisticated structure shaped by regulatory developments, technological advancements, and an expanding economic base. While rooted in global practices, auditing in Nigeria now reflects the unique socio-economic realities of the nation, including its informal sector, reliance on SMEs, and complex fiscal frameworks.

The Companies and Allied Matters Act (CAMA) 2020 remains a cornerstone of auditing practice in Nigeria. It mandates that all incorporated entities must produce audited financial statements annually. Public companies and financial institutions are further regulated by the Financial Reporting Council of Nigeria (FRCN) and the Central Bank of Nigeria (CBN), which enforce compliance with International Financial Reporting Standards (IFRS). These regulations align Nigerian auditing practices with global standards, promoting investor confidence and ensuring accountability.

Despite the formal framework, practical challenges persist. Regulatory oversight often intersects with systemic inefficiencies, and enforcement of audit-related policies is uneven, particularly outside urban centers. The presence of two major professional bodies, ICAN and ANAN, has also occasionally created tensions over jurisdiction and standardization, although collaborative efforts in recent years aim to harmonize professional standards.

Nigeria today integrates a mix of traditional and modern approaches. Field audits, characterized by manual checks of records, remain common, particularly among SMEs that lack robust digital infrastructure. At the same time, larger firms increasingly adopt technology-driven practices, including automated data analysis and forensic accounting tools, to enhance audit accuracy and efficiency.

The growth of forensic auditing, particularly in response to corruption and financial crimes, underscores the evolving demands of the profession. Forensic auditing, driven by heightened regulatory scrutiny and corporate governance reforms, has become a critical area of practice. Auditors now play a proactive role in detecting fraud and ensuring compliance with anti-corruption frameworks, particularly in sectors such as banking and oil and gas, where financial irregularities are historically prevalent.

The challenges facing auditing In Nigeria are multi-faceted. Corruption remains a significant concern, influencing both public and private sector audits. Instances of "opinion shopping," where clients pressure auditors for favorable reports, compromise the profession's integrity. Additionally, economic instability, marked by fluctuating exchange rates and inflation, complicates the valuation of assets and liabilities.

Another notable issue is the lack of technological adoption among many Nigerian firms. While global auditing practices leverage artificial intelligence and data analytics for efficiency and fraud detection, many businesses in Nigeria operate on paper-based systems, limiting the scope of modern audit techniques. For SMEs, cost constraints further hinder access to advanced audit services, perpetuating gaps in financial accountability.

The audit atmosphere in Nigeria is not just a regulatory requirement; it is integral to economic development. By ensuring transparency in financial reporting, audits enhance investor confidence and facilitate access to credit, particularly for SMEs that constitute a significant portion of the economy. In the public sector, auditing plays a crucial role in monitoring government expenditures and reducing waste. In recent years, the push for sustainability reporting has introduced new dimensions to auditing, with firms now expected to provide assurance on non-financial metrics, such as environmental impact and social responsibility. This shift aligns with global trends and positions Nigeria to participate in the broader discourse on corporate sustainability.

The audit practice in Nigeria reflects a dynamic interplay between traditional practices and modern demands. While the profession has made significant strides, systemic challenges persist, requiring continuous reform and investment. Bridging the technological divide, addressing corruption, and strengthening regulatory enforcement are critical for advancing auditing practices in the country. As Nigeria's economy integrates further into the global landscape, the role of auditing will remain pivotal in fostering accountability, enhancing investor confidence, and supporting sustainable growth.

2.1.4 Audit Efficiency

Audit efficiency is the ability of the auditing process to achieve its objectives effectively and economically, ensuring high-quality standards with minimal resources. This efficiency directly impacts the reliability of financial statements, regulatory compliance, and trust in organizational governance. By detecting errors, fraud, or misstatements quickly, efficient audits allow organizations to make informed decisions and maintain stakeholder confidence.

The concept of audit efficiency encompasses various dimensions, including time management, resource utilization, cost-effectiveness, and the accuracy of audit findings. In practice, it involves conducting audits in a way that minimizes delays and expenses, without compromising the depth and quality of the examination. Technological advancements such as audit software and data analytics tools have become essential for improving efficiency. These tools allow auditors to process large datasets rapidly, identify anomalies, and generate actionable insights with reduced manual effort.

Several factors influence audit efficiency. Technological adoption plays a crucial role, as innovations like artificial intelligence (AI), robotic process automation (RPA), and blockchain significantly enhance the audit process. These technologies enable real-time data analysis, automate repetitive tasks, and improve the accuracy of risk assessments. Additionally, the skillset and training of auditors are fundamental in ensuring efficiency. Ongoing professional development in emerging technologies and regulatory changes is key to maintaining effective audits. The regulatory environment also plays a part, as a well-defined framework ensures that audits are conducted transparently and systematically. However, overly stringent regulations can hinder efficiency, as auditors may spend more time meeting compliance requirements than focusing on the core tasks of the audit. Furthermore, the availability and accessibility of data are crucial; clean, organized data reduces analysis time, while incomplete or inconsistent data can cause delays. Finally, effective communication and collaboration between auditors and clients enhances audit efficiency. Timely access to documents and records, along with management input, contributes to a more efficient process.

In Nigeria, audit efficiency is becoming more important due to the increasing complexity of financial systems and growing scrutiny from regulatory bodies like the Financial Reporting Council of Nigeria (FRCN). The integration of technologies such as AI and data analytics is improving audit practices, though challenges remain, including inadequate infrastructure, limited technological literacy, and resistance to change. Additionally, the prevalence of fraud and financial mismanagement in both public and private sectors underscores the need for efficient audits to promote transparency and accountability. Initiatives like the Nigerian Code of Corporate Governance (NCCG, 2018) emphasize the importance of effective audits in ensuring good corporate governance. As the audit landscape continues to evolve, firms in Nigeria and globally are expected to rely increasingly on emerging technologies to improve efficiency. Fostering a culture of collaboration and training auditors in advanced analytical methods will be critical in overcoming the challenges associated with audit efficiency.

2.2 Key Areas of Artificial Intelligence in Auditing

Artificial intelligence (AI) continues to redefine auditing processes, enhancing precision, efficiency, and decision-making. Two significant AI innovations in auditing are Robotic Process Automation (RPA) and Predictive Analytics. These technologies streamline workflows, detect anomalies, and predict future trends, enabling auditors to focus on strategic insights while minimizing manual intervention.

2.2.1 Machine Learning and Auditing

Machine Learning, a subset of AI, uses algorithms to learn from data and improve performance without explicit programming. In auditing, ML plays a pivotal role in anomaly detection, risk assessment, and predictive analytics. It excels at identifying patterns and correlations within financial data, enabling auditors to pinpoint irregularities that may indicate fraud or mismanagement. For example, ML algorithms can analyze thousands of transactions in real-time, flagging outliers for further investigation (Wang & Cuthbertson, 2022).

One significant application of ML in auditing is risk-based auditing, where it helps allocate resources to high-risk areas by analyzing historical data and predicting potential problem zones. This approach reduces audit timelines and enhances audit quality. Another application is in automating the reconciliation of accounts, where ML models match complex transactions across multiple systems, significantly reducing manual effort (Kokina et al., 2019).

Advanced ML models, such as deep learning, are now being used to assess unstructured data like emails and contracts, providing auditors with insights that were previously inaccessible. For example, ML-powered tools like KPMG’s Ignite and Deloitte’s Cortex AI have transformed audit workflows, enabling auditors to process enormous volumes of data with improved precision (Brown et al., 2023).

Despite its benefits, the use of ML in auditing is not without challenges. Developing and training ML models requires substantial investment in technology and expertise. Additionally, concerns about data privacy and algorithmic bias must be addressed to ensure fair and reliable outcomes in audit procedures (Liu & Zhang, 2021).

2.2.2 Natural Language Processing (NLP) and Auditing

Natural Language Processing focuses on enabling machines to understand, interpret, and generate human language. In auditing, NLP enhances the review of textual data, such as contracts, emails, and audit reports, offering auditors the ability to extract relevant information efficiently. It reduces the time and resources spent on manual document reviews, enabling faster and more thorough audits (Vasarhelyi & Alles, 2020).

One critical application of NLP is contract analysis. Auditors can use NLP tools to identify key terms, clauses, and compliance requirements in large volumes of legal and financial documents. For instance, tools like MindBridge Ai Auditor and PwC's Halo for Contracts leverage NLP to scan and interpret contracts, flagging areas of potential risk or non-compliance (Amir et al., 2022).

Another transformative use of NLP is sentiment analysis, which examines the tone and sentiment of communications within an organization. This helps auditors assess organizational culture and potential ethical risks. For instance, detecting negative sentiment in internal communications could indicate a higher likelihood of financial misconduct or misreporting (Chen et al., 2021). NLP is also crucial in enhancing fraud detection by analyzing text-based communication for patterns of deceptive language. For example, subtle linguistic cues in emails can indicate fraudulent activities, providing auditors with additional layers of evidence (Ding et al., 2023).

While NLP has advanced significantly, challenges persist, particularly in understanding context and industry-specific terminologies. Developing domain-specific NLP models is critical for achieving accurate results, especially in industries with complex jargon and diverse financial practices.

2.2.3 Robotic Process Automation (RPA)

Robotic Process Automation (RPA) leverages software robots to automate repetitive and rule-based tasks, significantly improving audit efficiency. Unlike traditional automation, RPA can mimic human actions, such as logging into systems, extracting data, and performing reconciliations. In auditing, RPA serves as a critical tool for automating processes like journal entry testing, data aggregation, and compliance monitoring (Zhou et al., 2022).

One of the primary applications of RPA in auditing is transaction processing. For instance, robots can cross-check vast amounts of transactional data against pre-set audit criteria, flagging anomalies for review. This not only saves time but also reduces errors associated with manual reviews. Another critical use is in automating the extraction of financial data from disparate systems, which auditors can analyze without worrying about data inconsistencies (Appelbaum et al., 2021).

RPA also facilitates continuous auditing, allowing real-time analysis of financial transactions. This is particularly relevant in modern businesses with complex operations, as it enables auditors to identify risks promptly and provide timely recommendations. Deloitte's use of RPA in their audit solutions, for example, has shown improvements in accuracy and scalability of audit procedures (PwC, 2023).

Despite its transformative benefits, RPA implementation in auditing faces challenges. It requires significant initial investment, including software acquisition and employee training. Furthermore, RPA is best suited for structured tasks, meaning its efficacy may be limited in unstructured environments or complex audits requiring contextual understanding (Kokina & Davenport, 2020).

2.2.4 Predictive Analytics

Predictive analytics, another vital AI tool, uses statistical techniques and machine learning models to analyze historical data and predict future outcomes. This capability is instrumental in audit planning and risk assessment, as it enables auditors to anticipate potential risks and anomalies before they occur. Predictive analytics is particularly valuable in assessing trends in financial data, helping organizations to forecast performance and detect early signs of fraud or inefficiencies (Vasarhelyi et al., 2021).

One of the most impactful applications of predictive analytics in auditing is fraud detection. Predictive models analyze patterns in financial transactions to identify irregularities that may indicate fraudulent activities. For example, auditors can use predictive algorithms to detect unusual vendor behavior or inconsistencies in payroll data, flagging potential areas of concern for further investigation (Chiu et al., 2022).

Another area where predictive analytics shines is in improving audit sampling techniques. By analyzing historical data, auditors can identify high-risk transactions or accounts that require closer scrutiny, thereby enhancing the effectiveness of the audit process. Tools like IBM's Watson and MindBridge Ai Auditor have integrated predictive capabilities to assist auditors in this regard (Brown et al., 2023).

Predictive analytics also supports strategic decision-making by providing insights into long-term financial trends. Auditors can leverage these insights to advise clients on risk mitigation and financial planning. However, the accuracy of predictive models depends heavily on the quality of input data and the sophistication of the algorithms used. Poor data quality or biased algorithms can lead to misleading predictions, potentially compromising audit quality (Chen & Zhao, 2020).

2.3 Relationship Between Artificial Intelligence and Audit Efficiency

The integration of artificial intelligence (AI) into auditing has profoundly transformed the profession by enhancing the accuracy, efficiency, and effectiveness of audit processes. This relationship is underpinned by AI's ability to process large datasets, identify patterns, and perform repetitive tasks with minimal human intervention, enabling auditors to focus on higher-value activities. The synergy between AI and audit efficiency lies in the automation of routine processes, improvement in risk assessment, fraud detection, and the provision of actionable insights.

AI optimizes audit efficiency by automating labor-intensive tasks such as data entry, reconciliation, and sampling. Traditional auditing methods often rely on manual checks and sample-based reviews, which are time-consuming and prone to human error. AI-powered tools, however, allow auditors to analyze entire datasets, reducing the risk of oversight and ensuring comprehensive audits (Appelbaum et al., 2021). For instance, machine learning algorithms can rapidly identify anomalies in financial transactions, flagging potential irregularities for further examination. This not only saves time but also increases the accuracy of audit findings.

The use of AI also enhances risk assessment, a critical component of audit efficiency. AI systems can analyze historical data and identify trends that signal potential risks. Predictive analytics, a subset of AI, is particularly effective in forecasting future risks by recognizing patterns that precede financial mismanagement or fraud. Such tools enable auditors to allocate resources more effectively, concentrating efforts on high-risk areas. For example, studies have shown that predictive models can improve the identification of risky transactions by up to 30% compared to traditional methods (Brown et al., 2023).

Fraud detection has been another major beneficiary of AI in auditing. Traditional methods of detecting fraud often involve extensive manual effort and rely on the auditor's expertise to identify red flags. In contrast, AI employs advanced analytics to detect fraudulent patterns, such as unusual transaction sequences or deviations from expected behaviors. Tools like MindBridge Ai Auditor and IBM Watson have demonstrated significant improvements in fraud detection rates, helping organizations mitigate financial losses and uphold compliance with regulatory standards (Chiu et al., 2022).

Furthermore, AI-driven tools enhance the communication and visualization of audit findings. Natural language processing (NLP) technologies can generate clear and concise audit reports, summarizing complex financial data for stakeholders. Visual analytics tools, powered by AI, enable auditors to present data in intuitive formats, such as interactive dashboards, facilitating better decision-making. By improving the accessibility and clarity of audit results, AI fosters greater transparency and trust in the audit process (Kokina & Davenport, 2020).

Despite its many advantages, the relationship between AI and audit efficiency is not without challenges. The implementation of AI requires significant investment in infrastructure, training, and adaptation of existing workflows. Additionally, ethical concerns such as data privacy and algorithmic bias must be addressed to ensure fair and accurate audits (Chen & Zhao, 2020). The success of AI in enhancing audit efficiency ultimately depends on its integration into a well-designed audit framework, supported by skilled professionals capable of interpreting AI-generated insights.

Globally, the adoption of AI in auditing continues to grow, with leading firms such as Deloitte, PwC, and KPMG investing heavily in AI technologies to streamline their audit processes. In Nigeria, the impact of AI is gradually becoming evident as firms adopt AI-powered tools to cope with increasing regulatory demands and complex business environments. Although still in its nascent stage, the application of AI in Nigeria's auditing sector holds significant promise for improving audit quality and efficiency, particularly in addressing systemic challenges like fraud and tax evasion (Okafor et al., 2022).

The interplay between AI and audit efficiency represents a paradigm shift in the profession. By automating mundane tasks, enhancing risk assessment, and improving the accuracy of audits, AI empowers auditors to focus on strategic advisory roles, thereby increasing their value to clients and stakeholders. As AI technologies continue to evolve, their impact on audit efficiency will likely become even more profound, shaping the future of the profession.

2.4 Challenges of Integrating AI in Auditing

The integration of artificial intelligence (AI) into auditing presents transformative potential, yet it is not without significant challenges. These challenges span technical, organizational, ethical, and regulatory domains, each of which has implications for the successful deployment and utilization of AI in the auditing profession.

One of the most pressing technical issues in integrating AI is the requirement for high-quality, structured data. Auditing often involves analyzing data from disparate sources, many of which may be unstructured, incomplete, or incompatible with AI systems (Appelbaum et al., 2021). Preparing such data for AI processing involves extensive cleaning and transformation, which can be resource-intensive. Furthermore, the robustness of AI systems in handling anomalies or unexpected data patterns is another concern. These limitations can lead to inaccuracies in audit outputs, undermining the reliability of AI-driven analyses. There's yet again another technical hurdle is the "black-box" nature of many AI algorithms, especially deep learning models. These systems often provide results without clear explanations of how decisions were made, which conflicts with the transparency requirements of auditing. This opacity can create difficulties for auditors in justifying AI-generated findings to stakeholders, regulators, or legal bodies (Brown et al., 2023).

Adopting AI in auditing demands a substantial investment in infrastructure, training, and system integration. For many auditing firms, particularly small and medium-sized enterprises (SMEs), the cost of acquiring and maintaining AI tools is prohibitively high (Kokina & Davenport, 2020). Additionally, there is often resistance to change within organizations, with employees concerned about job displacement or skeptical of the benefits AI offers. Effective change management strategies are therefore critical but not always adequately implemented.

Another organizational challenge lies in the lack of skilled professionals who can operate and interpret AI systems effectively. While AI can automate certain tasks, its outputs often require human judgment and contextual understanding. The current workforce in the auditing sector may not possess the requisite technical skills, such as programming or data science expertise, to collaborate effectively with AI technologies (Chiu et al., 2022).

AI systems raise significant ethical concerns, particularly regarding data privacy and security. The sensitive nature of financial and organizational data makes its protection a paramount concern in auditing. Instances of data breaches or misuse of AI-generated insights can severely damage client trust and organizational reputation (Chen & Zhao, 2020). Additionally, biases embedded in AI algorithms can lead to discriminatory practices, such as unfairly targeting certain transactions or entities for scrutiny based on skewed historical data.

Legal frameworks governing AI usage in auditing remain underdeveloped in many regions, including Nigeria. There is an ongoing lack of clarity about liability in cases where AI-driven audits result in errors or oversights. This legal ambiguity complicates the adoption process, as firms must navigate uncertain regulatory environments (Okafor et al., 2022).

In Nigeria, the adoption of AI in auditing is further hampered by infrastructural deficiencies, such as unreliable power supply and limited access to high-speed internet. These constraints pose significant barriers to the deployment of cloud-based AI tools or real-time analytics systems. Additionally, many Nigerian auditing firms lack the financial capacity to invest in advanced AI technologies, leaving them dependent on manual processes that are less efficient and prone to human error.

The regulatory environment In Nigeria, while evolving, is still playing catch-up with the pace of technological advancement. Policymakers have yet to establish comprehensive guidelines for AI use in auditing, creating uncertainty for firms considering adoption. Compounding this issue is the scarcity of localized AI solutions tailored to the Nigerian business environment, which often features unique accounting practices and regulatory requirements (Okoye et al., 2023).

Despite these challenges, the auditing profession is increasingly recognizing the value of AI as a tool for enhancing audit quality and efficiency. Addressing the barriers to integration will require a multi-faceted approach. Investment in training programs to upskill auditors, collaboration with AI developers to create transparent and explainable systems, and active engagement with policymakers to establish clear regulations are essential steps. For Nigeria, targeted government support, such as subsidies for technology adoption and incentives for AI innovation, could significantly accelerate progress in this domain.

The integration of AI in auditing is a complex but necessary evolution. By overcoming these challenges, the profession can unlock the full potential of AI to deliver more accurate, efficient, and insightful audits, ultimately strengthening organizational accountability and public trust.

2.5 Theoretical Framework

Theoretical frameworks enrich a study by providing established models to understand and interpret phenomena. Building upon the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) Theory, this section integrates two additional theories, the Socio-Technical Systems (STS) Theory and the Unified Theory of Acceptance and Use of Technology (UTAUT). These frameworks complement the conceptual exploration of artificial intelligence (AI) adoption in auditing and deepen our understanding of the interplay between technology, individuals, and organizational dynamics.

2.5.1 Anchoring Bias Theory

The Anchoring Bias Theory, originally introduced by Tversky and Kahneman (1974), explains how individuals rely heavily on initial information (the "anchor") when making decisions. This cognitive bias affects judgment and decision-making by causing individuals to give disproportionate weight to the first piece of information encountered, even when it may be irrelevant or misleading.

Shifting specifically to audit efficiency, anchoring bias can influence auditors' assessments, particularly when evaluating financial statements, risk assessments, and anomalies in corporate reports. Auditors may become anchored to prior expectations, historical financial data, or management's explanations, leading to a risk of insufficient professional skepticism. For instance, if an auditor reviews a company's previous financial reports indicating stable profitability, they may be less likely to scrutinize new fluctuations critically, potentially overlooking signs of financial misstatements or fraud.

This theory is highly relevant to the integration of advanced audit technologies, such as Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics, in enhancing audit efficiency. These technologies can help mitigate anchoring bias by providing objective, data-driven insights rather than relying on subjective human judgment. By leveraging automation and predictive models, auditors can perform deeper analytical reviews, reducing the likelihood of errors caused by cognitive biases.

Anchoring Bias Theory thus 1supports the argument that incorporating advanced technologies in auditing can improve efficiency by reducing human biases and enhancing data-driven decision-making. This aligns with the study's objective of examining the role of AI-driven tools in modern auditing.

2.5.2 Agency Theory

Agency theory, developed by Jensen and Meckling (1976), provides a foundational framework for understanding the role of auditing in corporate governance. The theory describes the relationship between two key parties: the principal (such as shareholders or investors) and the agent (such as company management). In this relationship, principals delegate decision-making authority to agents, expecting them to act in the best interests of the firm. However, due to differing interests and asymmetric information, conflicts—known as agency problems—can arise, leading to opportunistic behavior by agents, such as earnings manipulation, fraud, or inefficient resource allocation.

Auditing, as an independent assurance mechanism, helps mitigate agency problems by reducing information asymmetry between managers and stakeholders. Traditionally, auditors examine financial statements to provide credibility and ensure compliance with regulatory standards. However, with the integration of Artificial Intelligence (AI) in auditing, the monitoring function has significantly improved. AI enhances fraud detection, automates data analysis, and increases audit efficiency, thereby strengthening corporate accountability and minimizing agency costs. The agency theory also explains why firms invest in high-quality audits to maintain investor confidence and reduce the cost of capital. The adoption of AI-driven auditing tools aligns with this rationale, as they provide greater accuracy, faster processing, and improved risk assessments. By leveraging AI, auditors can analyze large datasets, detect anomalies, and provide real-time insights, ultimately reinforcing transparency and trust in financial reporting.

Thus, agency theory remains a vital theoretical lens for understanding the impact of AI on audit efficiency. It underscores the necessity of robust audit mechanisms to safeguard stakeholder interests, maintain corporate integrity, and improve financial decision-making.

2.6 Empirical Review

Empirical studies on the integration of artificial intelligence (AI) in auditing highlight diverse findings, focusing on its impact on audit efficiency, fraud detection, and decision-making processes. This section reviews recent empirical research to synthesize insights, reveal trends, and establish a foundation for understanding AI's role in contemporary auditing practices.

Empirical evidence demonstrates that AI significantly enhances audit efficiency by automating routine tasks, reducing errors, and enabling auditors to focus on high-value activities. For instance, a study by Kokina and Davenport (2017) found that AI tools such as machine learning algorithms reduce the time spent on data analysis by up to 70%, allowing auditors to allocate more time to interpretive and judgment-based tasks. Similarly, Sirois et al. (2020) examined AI implementation in large audit firms and reported a 50% reduction in manual errors during data entry and sampling. In Nigeria, research by Okoye et al. (2023) revealed that mid-tier auditing firms leveraging AI tools experience improved fraud detection rates and reduced operational costs. However, the study noted challenges related to infrastructure and resistance to change among auditors. These findings are consistent with global trends, underscoring the transformative potential of AI when adequately supported by infrastructure and training.

Ayodele et al. (2021) also conducted a study on the adoption of AI in small and medium-sized audit firms, revealing an average time savings of 45% during audit planning stages. The study highlighted tools like machine learning and predictive analytics as instrumental in reducing errors and enabling auditors to focus on higher-value tasks, such as risk assessment and decision-making.

Existing works highlight AI's role in enhancing fraud detection and risk assessment. For instance, Gepp et al. (2018) analyzed the use of machine learning in detecting fraudulent transactions and found that these models outperform traditional statistical methods in accuracy and efficiency. A Nigerian case study by Adetunji et al. (2022) demonstrated that AI-driven tools like predictive analytics help auditors identify anomalies in financial statements, with a 35% higher detection rate compared to conventional methods. Global trends also point to the adoption of AI for continuous auditing. Appelbaum et al. (2020) reported that AI-enabled continuous monitoring systems reduce audit lag and enhance real-time fraud detection. However, the study cautioned against over-reliance on AI, emphasizing the importance of human oversight to interpret complex patterns and contextual anomalies.

Further, an investigation by Obinna and Ekene (2022) focused on AI-enabled continuous auditing systems in Nigerian financial institutions. The research highlighted the ability of these systems to provide real-time insights into financial anomalies, significantly reducing the detection-to-response time for fraud cases. This aligns with studies by Alles (2020), which emphasize the role of continuous auditing in enhancing transparency and accountability.

Despite its potential, the adoption of AI in auditing faces significant hurdles. Studies consistently identify issues such as data privacy, algorithmic biases, and the high cost of implementation as barriers. For example, a survey by PwC (2022) revealed that 65% of auditing firms in developing countries, including Nigeria, cite budget constraints as a major limitation. Furthermore, ethical concerns about the transparency of AI algorithms have been highlighted in works like Binns et al. (2018), which argue for the need for robust regulatory frameworks to ensure accountability.

AI integration is not without its challenges. Research by Marinova et al. (2021) examined the ethical implications of AI in auditing, highlighting concerns about algorithmic biases and transparency. The study called for robust regulatory frameworks to address these issues, emphasizing the need for audit firms to adopt ethical AI practices. Similarly, Adebayo et al. (2022) identified operational barriers, such as inadequate infrastructure and high implementation costs, as key obstacles to AI adoption in Nigerian audit firms.

Recent empirical research underscores emerging trends in AI integration, such as the use of natural language processing (NLP) for document review and robotic process automation (RPA) for repetitive tasks. A study by Brown et al. (2023) highlighted the growing use of RPA in Nigerian audit firms for tasks like invoice processing and reconciliation. The findings indicated a 60% increase in task efficiency among firms that adopted these technologies.

2.7 Gap in Existing Literature

The existing body of research on artificial intelligence (AI) in auditing has revealed significant advancements but also notable gaps that align with the objectives of this study.

While many studies have demonstrated AI's potential in improving efficiency, fraud detection, and risk assessment, there remains insufficient exploration of its applicability to small and medium-sized enterprises (SMEs). Research such as that by Ayodele et al. (2021) highlights the challenges SMEs face, including budgetary constraints and lack of expertise, but fails to propose comprehensive, scalable solutions tailored to smaller firms. This gap is critical given the significant role SMEs play in developing economies like Nigeria.

Most of the existing literature frequently prioritizes the technical capabilities of AI tools over their implications for auditors' skill sets and roles. While Liu et al. (2021) emphasize efficiency gains from AI adoption, there is limited discussion on the professional development required for auditors to adapt to AI-driven processes. This gap underscores the need for more detailed investigations into the intersection of human and machine collaboration within auditing practices.

Another area lacking sufficient attention is the long-term impact of AI integration in auditing. While studies such as those by Zhang et al. (2021) and Nguyen and Cao (2022) document short-term benefits, few have evaluated the sustainability of these gains over time, especially in contexts with dynamic regulatory and economic landscapes. This is particularly important in countries like Nigeria, where technological infrastructure and regulatory frameworks are still evolving.

The socio-cultural and regulatory challenges unique to specific regions, including Nigeria, are often underexplored. Although Obinna and Ekene (2022) address some of these factors, existing studies generally fail to provide actionable recommendations for overcoming region-specific barriers to AI adoption. This gap is particularly relevant for fostering equitable access to AI technologies and ensuring that local auditing practices can leverage global advancements effectively.

This study seeks to address these gaps by focusing on the Nigerian auditing landscape, exploring how AI can be integrated into auditing processes within SMEs, and analyzing its implications for skill development and regulatory compliance. By bridging these gaps, the research aims to provide practical insights that contribute to the broader understanding of AI adoption in auditing while ensuring its relevance to local contexts.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter outlines the methodology used to achieve the objectives of the study, focusing on exploring the relationship between artificial intelligence (AI) and audit efficiency. It details the research design, population and sampling techniques, sample size, and methods of data collection and analysis. Each section is structured to ensure clarity, relevance, and alignment with the research objectives, providing a strong foundation for empirical validation.

3.2 Research Design

The study employs a survey research design, which is well-suited to obtaining data from a wide range of respondents and analyzing their perspectives. Survey research, as defined by McCombes (2023), involves collecting and interpreting information about a group of people through structured questions. This design is appropriate for this study as it allows for the systematic collection of quantitative and qualitative data to understand the impact of AI on audit efficiency. Additionally, surveys offer flexibility in reaching diverse respondents, particularly professionals in auditing and related fields.

3.3 Population of the Study

The population of this study includes professionals from various industries in Benin City, Nigeria, such as accounting firms, corporate finance departments, and public service organizations of which consist a total number of 19 (see appendix)

This heterogeneous list was chosen due to their varying degree of artificial intelligence adoption in their auditing process. Focusing on Benin City allows for the inclusion of respondents with diverse perspectives, reflecting the varying levels of AI adoption and audit practices.

3.4 Sample Size and Sampling Technique

The sample for this study consists of 50 respondents selected randomly to represent the industries chosen in the population of the study using simple random sampling technique.

3.5 Validity and Reliability of Instruments

The validity and reliability of the instruments used in this research were carefully tested to ensure that they effectively capture the critical variables required for analyzing the relationship between artificial intelligence and audit efficiency. To establish content validity, the questionnaire was developed with input from the research supervisor and industry professionals with expertise in AI and auditing. The survey items were designed to address key areas such as automation capabilities, accuracy of financial reporting, and operational challenges in AI adoption.

A trial run of the questionnaire would be conducted with a group of respondents chosen from the target population prior to full-scale implementation. The purpose of this trial run was to evaluate the survey items' relevancy, clarity, and comprehensibility. The modifications that were required to strengthen the instrument's validity and efficacy were made in response to the input received from pilot participants. Through these adjustments, the questionnaire items were guaranteed to effectively connect with the respondents, eliciting their viewpoints and experiences regarding the effects of artificial intelligence on auditing.

3.6 Method of Data Collection

The research will utilize a questionnaire as its primary tool for data collection. This questionnaire comprises two distinct sections. The initial segment aims to gather biographical details, encompassing age, gender, level of education, and work history. Conversely, the subsequent section presents inquiries structured using a five-point Likert scale, prompting participants to provide their responses. Also, the result was used to answer the research questions and test the relevant hypotheses.

3.7 Method of Data Analysis

To show the relationship between one or more independent quantitative variables and a dependent variable, data analysis will use linear regression. By using this statistical method, it is best to find a straight line that closely matches the data points. Most people agree that the best optimization technique for getting objective estimates of alpha and beta is linear regression. When mistakes have finite variances, it produces mean-unbiased estimates with low variance. SPSS 20.0, the Statistical Package for Social Science, will be used to analyze the data.

3.8 Model Specification

The model used in this study is adapted from the research framework established by (Owonifari et al., 2023), which examined the impact of artificial intelligence in Audit practice of small scale from using ikeja as its case study. To align the model with the study's focus on AI in auditing, modifications were made to reflect the specific variables and objectives of this research.

The model is expressed as:

$Y=f(X1,X2,X3,X4)$

The regression equation is:

$Y=\beta0+\beta1X1+\beta2X2+\beta3X3+\beta4X4+\epsilon$

Where:

- Y = Audit efficiency
- X_1 = Machine Learning
- X_2 = Natural Language Processing (NLP)
- X_3 = Robotic Process Automation (RPA)

- X_4 = Predictive Analytics
- β_0 = Intercept
- β_1–β_4 = Coefficients for the independent variables
- $\boldsymbol{\varepsilon}$ = Error term

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION

4.1 Introduction

This chapter deal with the presentation and analysis of data collected from the study application to examine the relationship between AI and Audit efficiency. The collected data were processed using Statistical Package for Social Sciences (SPSS 20.0), and the analysis was conducted through descriptive and inferential statistical techniques. Specifically, linear regression analysis was employed to assess the impact of AI components—Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics—on audit efficiency.

The chapter is structured as follows: First, a preliminary analysis of the demographic characteristics of respondents is presented. This is followed by a descriptive analysis of key research variables to summarize their distribution and trends. Next, inferential statistical techniques, including regression analysis, are applied to test the research hypotheses. Finally, the findings are interpreted in line with the study's objectives, providing empirical insights into the role of AI in audit processes.

4.2 Data Presentation

Table 4.1 Descriptive Statistics

	X1	*X2*	*X3*	*X4*	*Y*
Mean	3.6702703	3.8702703	3.8054054	3.5900901	3.6648649
Standard Error	0.1382465	0.1025841	0.1596705	0.141874	0.1414328
Median	3.8	4	4	3.6666667	3.8
Mode	3	4	3	3	3
Standard Deviation	0.8409204	0.6239947	0.971238	0.8629859	0.8603023
Sample Variance	0.7071471	0.3893694	0.9433033	0.7447447	0.7401201
Kurtosis	1.4849435	-0.759392	5.2244907	7.4307524	1.350954
Skewness	-0.819911	-0.003848	-1.61435	-1.738122	-0.657974
Range	4	2.2	5	5	4
Minimum	1	2.8	0	0	1
Maximum	5	5	5	5	5
Sum	135.8	143.2	140.8	132.83333	135.6
Count	37	37	37	37	37

Source: Researcher's Computation (2025)

The descriptive statistics provide an overview of the dataset, summarizing key characteristics of the dependent variable, audit efficiency (Y), and the independent variables: machine learning (X_1), natural language processing (X_2), robotic process automation (X_3), and predictive analytics (X_4). The mean values for these variables range between 3.59 and 3.87, indicating that the majority of responses clustered around these values. The median values closely align with the mean, suggesting that the data distribution is relatively symmetric for most variables. Additionally, the mode, which represents the most frequently occurring value, reinforces this observation, showing consistency in responses.

The degree of variability in the dataset is reflected in the standard deviation values, which range from 0.62 (X_2) to 0.97 (X_3). The higher standard deviations, particularly for X_3 (robotic process automation) and X_4 (predictive analytics), suggest that responses for these variables exhibit more spread compared to others. This observation is further supported by the sample variance, which follows a similar pattern. The range of values, spanning from 2.2 (X_2) to 5 (X_4), indicates that some variables exhibit a wider spread of responses, with X_4 (predictive analytics) showing the highest variability.

Examining the distributional properties, the skewness values reveal that most variables exhibit a slight left-skewed distribution, except for X_2 (natural language processing), which is nearly symmetric. The strongest skewness is observed in X_3 (-1.614) and X_4 (-1.738), indicating that these variables have a longer left tail, meaning a small number of lower values influenced the distribution. The kurtosis values provide additional insights into the shape of the distribution. X_3 (5.22) and X_4 (7.43) have high kurtosis values, indicating that their distributions are more peaked and have heavier tails, suggesting potential outliers. In contrast, X_2 (-0.75) has a lower kurtosis, indicating a relatively flatter distribution.

The minimum and maximum values further clarify the data spread, with minimum values ranging from 0 to 2.8 and maximum values around 5 for most variables. The presence of a zero value for X_4 (predictive analytics) suggests that some respondents reported no adoption or minimal reliance on predictive analytics in auditing. This variability across the independent variables highlights differences in how machine learning, NLP, RPA, and predictive analytics are integrated into audit processes.

The descriptive statistics indicate moderate variability, with robotic process automation (X_3) and predictive analytics (X_4) showing the most significant deviations from a normal distribution due to their skewness and peaked distributions. The central tendency measures suggest that responses are generally consistent, but the presence of outliers in some variables might influence further statistical analysis. These insights provide a foundation for the next stage of the research, which involves inferential analysis to determine how these AI-driven tools contribute to enhancing audit efficiency.

4.3 Presentation of Demographics

The demographic characteristics of the respondents provide critical insights into their backgrounds, which may influence their perceptions of audit efficiency and the role of artificial intelligence (AI) technologies in auditing. Understanding these factors is essential for contextualizing the study's findings and assessing how different groups interact with technologies such as Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics.

Table 4.2 Gender Distribution of Respondents

Gender	*Frequency*	*Percent*	*Cummulative Percent*
Female	20	54%	65%
Male	17	46%	100%
Grand Total	37	100%	

Source: Researcher's Computation (2025)

The data reveals that 54% of the respondents are female (20 individuals), while 46% are male (17 individuals). This relatively balanced gender representation suggests that perspectives on audit efficiency and AI adoption are gathered from both genders, ensuring that the findings are not skewed toward a single demographic. Given the increasing presence of women in finance, accounting, and technology-related fields, this distribution reflects the evolving nature of the workforce in these domains. The responses may offer insights into whether gender differences play a role in perceptions of AI-driven auditing.

Table 4.3 Age distribution of Respondents

Age-Group	*Frequency*	*Percent*	*Cummulative Percent*
18-25	25	68%	68%
26-45	12	32%	100%
Grand Total	37	100%	

Source: Researcher's Computation (2025)

A majority of respondents (68%) fall within the 18–25 age range, while 32% are between the ages of 26 and 45. This indicates that most participants are relatively young, which is significant for this study as younger professionals are generally more open to adopting emerging technologies. Their familiarity with AI-driven tools may contribute to a more optimistic outlook on how technologies like RPA and NLP can enhance audit efficiency. Conversely, the older segment of respondents may provide perspectives on the practical challenges and limitations of integrating these technologies into traditional auditing processes.

Table 4.4 Educational Distribution of Respondents

Education Level	***Frequency***	***Percent***	***Cummulative Percent***
HND/Bsc	25	68%	68%
Masters/Ph.D	1	3%	70%
Professional Qualification	3	8%	78%
SSCE/GCE	8	22%	100%
Grand Total	37	100%	

Source: Researcher's Computation (2025)

The education distribution shows that 68% of respondents hold an HND/BSc degree, while only 3% have a Master's or Ph.D., and 8% possess professional qualifications. Additionally, 22% have an SSCE/GCE qualification. This educational background is crucial to the study, as individuals with higher educational attainment are more likely to understand and engage with AI applications in auditing. The predominance of respondents with at least a tertiary education suggests that the sample is well-equipped to assess the impact of advanced analytics and automation on audit processes. Those with professional qualifications may provide industry-specific insights into AI's practical applications and challenges in auditing.

Table 4.5 Nature of Work distribution among Respondents

Nature of Work	***Frequency***	***Percent***	***Cummulative Percent***
Managerial	7	19%	19%
Non-Managerial	30	81%	100%
Grand Total	37	100%	

Source: Researcher's Computation (2025)

The majority of respondents (81%) are in non-managerial roles, while 19% hold managerial positions. This distinction is important as it reflects a workforce that is primarily responsible for the execution of audit tasks rather than strategic decision-making. Employees in non-managerial roles are often the primary users of AI-driven audit tools, making their perspectives valuable in assessing the practical usability and efficiency of these technologies. Meanwhile, managerial respondents can offer insights into how AI adoption impacts overall audit strategy, compliance, and risk management.

Table 4.5 Income Level Distribution of Respondents

Income Level	*Frequency*	*Percent*	*Cummulative Percent*
200,000 and above	10	27%	27%
50,000 and below	21	57%	84%
60,000-100,000	6	16%	100%
Grand Total	37	100%	

Source: Researcher's Computation (2025)

A significant portion of respondents (57%) earn ₦50,000 and below, 16% fall within the ₦60,000–₦100,000 range, while 27% earn ₦200,000 and above. This distribution is relevant to the study as income levels often correlate with job roles, responsibilities, and access to technology. Lower-income respondents, who are likely in entry-level positions, may have firsthand experience with AI-driven audit processes but limited decision-making power regarding their adoption. In contrast, higher-income respondents, who are likely in managerial or specialized roles, may provide insights into how AI-driven auditing affects organizational efficiency, cost savings, and strategic planning.

4.4 Pearson Correlation Coefficient

Table 4.6 Correlation Summary

	Y	*X1*	*X2*	*X3*	*X4*
Y	1				
X1	0.847462	1			
X2	0.637047	0.646751	1		
X3	0.782811	0.883803	0.620869	1	
X4	0.898594	0.831854	0.557058	0.83898	1

Source: Researcher's Computation (2025)

The correlation analysis examines the relationships between audit efficiency (Y) and the independent variables: Machine Learning (X_1), Natural Language Processing (NLP) (X_2), Robotic Process Automation (RPA) (X_3), and Predictive Analytics (X_4). The strength and direction of these relationships provide insights into how technological advancements contribute to audit efficiency.

The correlation between Machine Learning (X_1) and audit efficiency (Y) is 0.847, indicating a strong positive relationship. This suggests that as machine learning is integrated into audit processes, efficiency is likely to improve significantly. Natural Language Processing (X_2) has a correlation of 0.637 with audit efficiency, which is a moderately strong positive relationship. This implies that while NLP contributes to efficiency, its impact may be slightly less pronounced than machine learning.

Robotic Process Automation (X_3) also exhibits a strong positive correlation with audit efficiency, with a coefficient of 0.783. This suggests that RPA plays a crucial role in automating repetitive audit tasks, enhancing accuracy and speed. Predictive Analytics (X_4) shows the highest correlation with audit efficiency at 0.899, implying that the ability to forecast risks and anomalies significantly enhances audit effectiveness.

The correlations among the independent variables indicate strong relationships, particularly between Machine Learning (X_1) and RPA (X_3) (0.884), and between RPA (X_3) and Predictive Analytics (X_4) (0.839). These values suggest that these technologies are often implemented together, reinforcing their collective impact on audit efficiency.

The analysis confirms that all four technological factors positively influence audit efficiency, with Predictive Analytics (X_4) having the strongest relationship. These findings highlight the importance of integrating data-driven technologies in audit processes to enhance performance and reliability.

4.5.1 Analysis of Regression Results

Table 4.7 Ordinary Least Square Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.926139
R Square	0.857734
Adjusted R Square	0.83995
Standard Error	0.344174
Observations	37

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	22.85373	5.713432	48.2325	4.15E-13
Residual	32	3.790595	0.118456		
Total	36	26.64432			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.2497	0.367135	-0.68012	0.501318	-0.99753	0.498133	-0.99753	0.498
X1	0.368773	0.161269	2.286704	0.028974	0.04028	0.697267	0.04028	0.6972
X2	0.203683	0.121702	1.67362	0.010395	-0.04422	0.451583	-0.04422	0.4515
X3	-0.18181	0.138915	-1.30878	0.199929	-0.46477	0.101151	-0.46477	0.101
X4	0.686505	0.130665	5.253926	9.49E-06	0.420349	0.952661	0.420349	0.9526

Source: Researcher's Computation (2025)

4.5.2 Hypothesis Testing

Hypothesis 1: Machine Learning has no significant positive impact on audit efficiency.

The first hypothesis states that Machine Learning has no significant positive impact on audit efficiency. Based on the regression results, the coefficient for Machine Learning (X_1) is 0.368773, indicating a positive relationship with audit efficiency. The corresponding p-value is 0.028974, which is below the 0.05 significance threshold. This suggests that Machine Learning has a statistically significant impact on audit efficiency. Therefore, the null hypothesis is rejected, meaning Machine Learning positively influences audit efficiency.

Hypothesis 2: Natural Language Processing (NLP) has no significantly affects on audit efficiency.

The second hypothesis asserts that Natural Language Processing (NLP) has no significant effect on audit efficiency. The regression analysis reveals that NLP (X_2) has a coefficient of 0.203683, implying a positive effect. However, the p-value is 0.10395, which is above the 0.05 significance level. This means the effect of NLP on audit efficiency is not statistically significant. As a result, the null hypothesis is not rejected, indicating that NLP does not have a significant impact on audit efficiency based on the given data.

Hypothesis 3: Robotic Process Automation (RPA) has played no significant role in enhancing audit

The third hypothesis posits that Robotic Process Automation (RPA) has played no significant role in enhancing audit efficiency. The regression output shows that RPA (X_3) has a coefficient of -0.18181, suggesting a negative relationship with audit efficiency. The p-value is 0.199929, which exceeds 0.05, meaning the effect Is not statistically significant. Consequently, the null hypothesis is not rejected, implying that RPA does not have a meaningful influence on audit efficiency in this study.

Hypothesis 4: Predictive Analytics has no significant influence on audit efficiency.

The final hypothesis states that Predictive Analytics has no significant influence on audit efficiency. The regression coefficient for Predictive Analytics (X_4) is 0.686505, indicating a strong positive effect. The p-value is 9.49E-06, which is significantly below 0.05, confirming that the effect is highly significant. Therefore, the null hypothesis is rejected, and we conclude that Predictive Analytics has a significant and positive impact on audit efficiency.

4.6 Discussion of Findings

The findings of this study provide critical insights into the role of emerging technologies in enhancing audit efficiency. The correlation analysis revealed strong positive relationships between the independent variables and audit efficiency, particularly for Machine Learning and Predictive Analytics. This aligns with previous research that highlights the increasing reliance on data-driven decision-making and predictive modeling in modern audit practices. The high correlation values suggest that these technologies are not only relevant but also integral to optimizing audit processes. However, the strength of correlation alone does not confirm causality, necessitating further analysis through regression modeling.

The regression analysis further refined these observations by assessing the statistical significance of each variable. The results indicate that Machine Learning and Predictive Analytics have significant positive effects on audit efficiency, as evidenced by their positive coefficients and low p-values. These findings suggest that firms leveraging these technologies experience improved accuracy, reduced audit risks, and enhanced fraud detection capabilities. Predictive Analytics, in particular, demonstrated the strongest impact, reinforcing its role in forecasting financial anomalies and optimizing audit procedures. This is consistent with studies emphasizing predictive modeling as a key driver of efficiency in financial auditing.

Conversely, the results for Natural Language Processing (NLP) and Robotic Process Automation (RPA) did not show statistically significant effects on audit efficiency. Although NLP has been recognized for its ability to process vast amounts of unstructured financial data, the findings suggest that its integration into audit workflows may still be evolving. Similarly, the negative coefficient for RPA implies that while automation reduces manual workload, its direct influence on audit efficiency may be contingent on factors such as implementation scale and organizational readiness. These results underscore the need for further research to explore how these technologies can be better integrated to maximize their benefits in audit functions.

The findings in this study reinforces the importance of advanced analytics in modern auditing while highlighting areas for further technological development. Organizations seeking to enhance audit efficiency should prioritize investments in Machine Learning and Predictive Analytics while refining their approach to NLP and RPA to achieve optimal outcomes. Future research could explore the interplay of these technologies in various audit environments, considering industry-specific challenges and adoption barriers.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION, AND RECOMMENDATIONS

5.1 Introduction

The integration of advanced technologies into auditing practices has become a transformative force in the accounting and financial sectors. Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics are reshaping the efficiency, accuracy, and effectiveness of audit procedures. This chapter presents a comprehensive summary of the research findings, draws insightful conclusions, and provides actionable recommendations that can enhance audit efficiency through technological adoption.

5.2 Summary of Findings

The objective of this study was to evaluate the impact of emerging technologies on audit efficiency. To achieve this, four key explanatory variables of which were Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics—were analyzed in relation to audit efficiency. The study utilized statistical techniques such as correlation analysis and regression modeling to assess these relationships based on empirical data.

Based on the analysis and evaluation of the research data, the following summary of findings has been derived and organized according to the hypotheses:

1. Machine Learning has a significant positive impact on audit efficiency.
2. Natural Language Processing (NLP) does not have a significant impact on audit efficiency.
3. Robotic Process Automation (RPA) has no significant role in enhancing audit efficiency.
4. Predictive Analytics has a significant positive influence on audit efficiency.

These findings highlight the varying impact of different emerging technologies on audit efficiency and underscore the need for firms to strategically implement these tools for maximum effectiveness.

5.3 Conclusion

This study explored the impact of emerging technologies—Machine Learning, Natural Language Processing (NLP), Robotic Process Automation (RPA), and Predictive Analytics—on audit efficiency. The motivation for this research stemmed from the increasing complexity of financial transactions, the growing volume of audit data, and the demand for more efficient and reliable audit processes. By reviewing relevant literature and analyzing empirical data, this study provided insights into how these technologies influence the audit function.

The findings revealed that Machine Learning and Predictive Analytics significantly enhance audit efficiency by improving fraud detection, anomaly identification, and risk forecasting. These technologies streamline data analysis and enable auditors to make more informed decisions. Conversely, NLP and RPA, though useful in automating tasks such as document reviews and data extraction, did not demonstrate a statistically significant impact on overall audit efficiency. While NLP aids in processing unstructured financial data and RPA automates repetitive audit procedures, their effectiveness appears to depend on contextual factors such as implementation strategies and organizational readiness.

The results highlight the need for firms to adopt a strategic approach to integrating these technologies into their audit processes. Proper training, infrastructure development, and continuous evaluation are essential to maximizing their benefits. Additionally, auditors must adapt to technological advancements by acquiring new skills and leveraging these tools effectively. Ultimately, this study underscores the transformative potential of emerging technologies in auditing, emphasizing that while they can enhance efficiency, their success depends on thoughtful implementation and continuous adaptation to evolving audit challenges.

5.4 Recommendations

Based on the findings of this study, the following recommendations are proposed to enhance audit efficiency through the effective adoption of emerging technologies:

1. **Investment in Technological Infrastructure:** Organizations should prioritize investing in advanced audit technologies such as Machine Learning, NLP, RPA, and Predictive Analytics. Adequate infrastructure, including cloud computing and secure data storage systems, is necessary to facilitate seamless integration.

2. **Training and Capacity Building:** Auditors should undergo continuous training to develop proficiency in using these technologies. Firms should organize workshops, certification programs, and hands-on training to ensure auditors can effectively leverage AI-driven tools.
3. **Customized Implementation Strategies:** The effectiveness of emerging technologies varies across firms and industries. Organizations should assess their specific audit needs and tailor the adoption of Machine Learning, NLP, RPA, and Predictive Analytics to align with their operational goals.
4. **Enhanced Data Governance and Security:** As technology adoption increases, firms must implement robust data governance policies to ensure data integrity, security, and compliance with regulatory standards. Proper safeguards should be in place to prevent data breaches and unauthorized access.
5. **Collaboration Between Auditors and IT Professionals:** Effective implementation of audit technology requires collaboration between auditors and IT specialists. Organizations should foster interdisciplinary teamwork to bridge the gap between audit expertise and technological innovation.
6. **Regulatory Framework:** Regulatory bodies should update audit guidelines to accommodate technological advancements. Clear policies on the ethical use of AI and automation in auditing should be established to maintain transparency and accountability.

7. **Continuous Monitoring and Evaluation:** Organizations should regularly assess the impact of technology on audit efficiency. Periodic performance reviews, feedback mechanisms, and adjustments to implementation strategies will help optimize the use of emerging technologies in auditing.

5.5 Suggestions for Further Research

To build on the findings of this study and explore emerging areas in audit technology, the following suggestions for further research are proposed:

1. **Exploring the Long-Term Impact of AI on Audit Quality:** More studies could examine the long-term effects of AI-driven audit tools on audit accuracy, fraud detection, and financial transparency across different industries.
2. **Comparative Analysis of Traditional vs. AI-Driven Auditing:** Research could compare audit efficiency between firms that have fully adopted AI-powered auditing and those still relying on traditional methods to assess performance differences.
3. **Ethical and Legal Implications of AI in Auditing:** Further research is needed to explore the ethical concerns, privacy risks, and regulatory challenges associated with using AI technologies in auditing.
4. **Adoption Barriers and Organizational Readiness:** Investigating the key challenges organizations face when implementing technologies like Machine Learning, NLP, and RPA in audit processes can provide insights into overcoming adoption barriers.

5. **Industry-Specific Application of Emerging Audit Technologies:** Future studies could focus on how AI-powered audit technologies impact specific industries such as banking, healthcare, or manufacturing, where financial reporting complexities vary.
6. **Human-AI Collaboration in Auditing:** Research could explore how auditors and AI can work together efficiently, identifying the optimal balance between automation and human judgment in the audit process.
7. **The Role of Blockchain in Enhancing Audit Integrity:** With the rise of blockchain technology, future studies could assess its integration with AI-driven audits to enhance transparency, fraud detection, and financial reporting accuracy.

These areas of further research will provide deeper insights into the evolving role of technology in auditing and contribute to the development of more effective and ethical auditing frameworks.

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APPENDIX

QUESTIONNAIRE

QUESTIONNAIRE ON THE EFFECT OF ARTIFICIAL INTELLIGENCE ON AUDIT EFFICACY

Department of Accounting,
Faculty of Management Sciences,
University of Benin City

Dear Sir/Madam,

REQUEST FOR RESPONSES FOR THE COMPLETION OF THIS QUESTIONNAIRE

I am [Your Full Name], a student of the above-named institution, and as part of the requirements of the academic program for the award of a B. Sc. Degree in Accounting, I am conducting a research project titled **"The Effec9 of Artificial Intelligence on Audit Efficacy"**, and you have been selected as part of the sample for this study.

I wish to appeal to you to kindly spare a few minutes to complete this questionnaire to the best of your knowledge. Be assured that your answers will be treated in strict confidence and used solely for academic purposes. Thank you for your cooperation.

Yours faithfully,

[Your Full Name]

Section A: Personal Data

Instruction: Kindly fill in the following questions by ticking [√] in the column of your choice.

1. **Gender:**
   a) Male [ ]
   b) Female [ ]
2. **Age Group:**
   a) 18-25 [ ]
   b) 26-45 [ ]
   c) 46-55 [ ]
   d) 56 and above [ ]
3. **Highest Educational Qualification:**
   a) SSCE/GCE [ ]
   b) HND/BSc [ ]
   c) Masters/Ph.D. [ ]
   d) Professional Qualification [ ]
4. **Nature of Work:**
   a) Managerial [ ]
   b) Non-Managerial [ ]
5. **Years of Experience in Auditing or Related Fields:**
   a) Less than 1 year [ ]
   b) 1-5 years [ ]
   c) 6-10 years [ ]
   d) Above 10 years [ ]

Section B: Research Questions

Instructions: Kindly select the option that most aligns with your view by indicating the extent to which you agree with the statements below.

NB:

SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree and SA = Strongly Agree

Section	Questions	SD	D	N	A	SA
Machine Learning and Audit Efficiency	1. Machine learning enhances the accuracy of financial audits.					
	2. Machine learning reduces the time required for audit processes.					
	3. Machine learning algorithms help detect fraud more efficiently.					
	4. The adoption of machine learning improves decision-making during audits.					
Natural Language Processing (NLP)	5. NLP simplifies the analysis of unstructured data during audits.					
	6. NLP tools improve the interpretation of financial documents in audits.					

	7. NLP enhances the ability to identify anomalies in financial records.					
	8. Implementing NLP tools increases audit efficiency in complex organizations.					
Robotic Process Automation (RPA)	9. RPA reduces human errors in auditing processes.					
	10. RPA accelerates repetitive tasks such as data entry in audits.					
	11. RPA improves compliance with regulatory standards in auditing.					
	12. RPA frees auditors to focus on higher-level analytical tasks.					
Predictive Analytics	13. Predictive analytics helps auditors foresee financial risks.					
	14. The use of predictive analytics enhances audit planning and strategy.					
	15. Predictive analytics tools provide valuable insights into					

	financial trends for audits.					
	16. Predictive analytics significantly improves the detection of fraudulent activities.					
Overall Effect of AI on Audit Efficiency	17. Artificial intelligence improves the overall quality of audits.					
	18. The integration of AI technologies significantly reduces audit costs.					
	19. AI adoption increases the reliability of audit outcomes.					
	20. Auditors with access to AI tools are better equipped to handle complex financial systems.					

Audit Firms in Benin City

List Of Audit and Financial Services Organizations in Benin City

S/N	Firm Name	Services Offered	Address
1	Olufola Abraham & Co.	Auditing, Tax, Management Consulting	24, Forestry Road, Benin City, Edo State
2	BBC Professionals	Auditing, Accounting, Tax, Insolvency, Financial and Management Consulting	6, Akpakpava Street, Benin City, Edo State
3	Abdulkerim Kadiri & Co.	Auditing, Advisory, Taxation, Consulting	90, Akpakpava Street, Benin City, Edo State
4	UHY Maaji & Co.	Audit, Assurance, Business Advisory	9, Monguno Road, Benin City, Edo State
5	Akinleye Olutayo & Co.	Auditing, Accounting, Tax Consulting	[Address not specified]
6	Partnership Investment Company	Financial Services, Stock Broking, Capital Raising, Wealth Management	Ring Road, Benin City, Edo State
7	Aims Asset Management	Financial Services, Equity Instruments	29, Sakponba Road, Benin City, Edo State
8	Myluxtrade Digital Hub	Financial Services, Digital Trading Solutions	

9	First Guide LLC	Financial Services, Business Improvement Solutions	

List of public services organizations in benin city

S/N	Organization Name	Services Offered	Address
1	John Odigie Oyegun Public Service Academy (JOOPSA)	Public service training and development Joopsa	1, Public Service Academy Road, Benin City, Edo State
2	Federal Neuro-Psychiatric Hospital, Benin City	Mental health services Wikipedia	1, Uselu Psychiatric Road, Benin City, Edo State
3	Ministry of Health	Public health services Edo State Government	Sapele Road, Benin City, Edo State
4	Ministry of Education	Educational administration and policy implementation Edo State Government	Iyaro, Benin City, Edo State
5	Ministry of Agriculture and Food Security	Agricultural development and food security initiatives Edo State Government	Sapele Road, Benin City, Edo State
6	Ministry of Justice/Attorney	Legal affairs and justice	Sapele Road, Benin

	General	administration Edo State Government	City, Edo State
7	Ministry of Water Resources	Water resource management Edo State Government	Sapele Road, Benin City, Edo State
8	Ministry of Communication and Orientation	Public communication and orientation services Edo State Government	Sapele Road, Benin City, Edo State
9	Ministry of Local Government, Community and Chieftaincy Affairs	Local government administration and community development Edo State Government	Sapele Road, Benin City, Edo State
10	Ministry of Public Security and Safety	Public security and safety services Edo State Government	Sapele Road, Benin City, Edo State