

ARTIFICIAL INTELLIGENCE AND AUDIT EFFICIENCY

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**A PROJECT SUBMITTED IN THE DEPARTMENT OF ACCOUNTING, FACULTY
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PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF B.Sc.
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DECLARATION

I hereby declare that this study was carried out by me in the Department of Accounting, University of Benin.

The study is original and has not been presented elsewhere for the award of any degree to the best of my knowledge. All ideas, opinions, and views were products of my personal research and were the views and contributions of other works and authorities have been used, they were duly acknowledged. Any form of error is entirely mine.

IGHODARO OSAYABAMWEN MARTHA

Project Student

Date

DEDICATION

I dedicate this project to God almighty for giving me the profound strength and wisdom to complete this project, and seeing me throughout my stay in the University of Benin.

CERTIFICATION

We the undersigned certify that this study is an original essay and was carried out by IGHODARO OSAYABAMWEN MARTHA, with the matriculation number MGS2104569, and that the research work is adequate in scope and quality in partial fulfilment of the requirements for the award of Bachelor of science (B.Sc.) Degree in Department of Accounting, Faculty of Management Sciences, University of Benin.

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Abstract

This study investigates the impact of Artificial Intelligence (AI) on audit efficiency within the private sector. The rapid advancement of AI technologies has transformed traditional auditing processes by enhancing data accuracy, speed, and decision-making. The objectives of this research are to examine the effect of AI on audit efficiency, evaluate the challenges auditors face in adopting AI-driven tools, ascertain the implications of AI integration on the future roles and skills required of auditors, and determine how AI supports auditors' professional judgment and decision-making during audits. The study adopts a quantitative research approach through the administration of structured questionnaires to auditors in selected private organizations. The data collected were analysed using descriptive and inferential statistical tools. Findings reveal that the adoption of AI significantly improves audit efficiency by automating repetitive tasks, reducing human error, and enabling real-time data analysis. However, the study also identifies key challenges, including high implementation costs, lack of technical expertise, data security concerns, and resistance to technological change. Furthermore, the integration of AI necessitates the acquisition of advanced digital and analytical skills among auditors to remain relevant in the evolving audit environment. The study concludes that while AI serves as a strategic tool for improving audit quality and efficiency, adequate training and organizational support are essential for its effective implementation

CHAPTER ONE

INTRODUCTION

Background to the Study

Artificial Intelligence (AI) has rapidly evolved over the past few decades, significantly transforming industries and societies worldwide. The concept of AI can be traced back to the pioneering work of Alan Turing in 1950, who proposed that machines could simulate intelligent behaviour (Turing, 1950). Since then, AI technologies have gained immense momentum across sectors such as healthcare, education, transportation, finance, and auditing. AI plays a crucial role in optimizing processes, enhancing decision-making, and improving efficiency across organizational functions (Binh et al., 2025). The growing integration of AI into business operations reflects a paradigm shift where technology is no longer viewed merely as a supplementary tool but as a strategic asset that drives competitiveness and innovation (Kokina & Davenport, 2017).

One area that has experienced significant transformation due to AI adoption is the audit function, which is central to corporate governance, accountability, and risk management (Chen, 2021). Traditionally, audit processes have relied heavily on manual evaluations and sample-based testing, both of which are time-consuming and susceptible to human error. Such limitations can reduce audit efficiency and delay critical decision-making (Earley, 2015). In contrast, AI technologies—such as machine learning (ML), natural language processing (NLP), and robotic process automation (RPA)—offer tools that can analyze large datasets, identify anomalies, and streamline audit tasks (Appelbaum, Kogan, & Vasarhelyi, 2017). These technologies enable auditors to test entire data populations instead of small samples, allowing for more comprehensive and accurate audit assessments.

For instance, machine learning algorithms can identify patterns indicative of fraud by processing large volumes of transactional data across multiple parameters (Binh et al., 2025). AI-based analytics tools also allow auditors to focus more on judgment-oriented tasks, thereby improving both efficiency and quality. Kokina and Davenport (2017) note that AI does not merely automate auditing processes but enhances the auditor's capacity to detect irregularities, assess risks, and improve audit outcomes.

Despite these promising advantages, the adoption of AI in auditing remains uneven, particularly in the private sector. Several challenges hinder full integration, including high implementation costs, lack of technical expertise, data quality issues, and resistance to organizational change (Krieger et al., 2021). Moreover, auditors often express concerns about the reliability, transparency, and explainability of AI-generated outputs, which may affect professional judgment and accountability (Kokina, 2025). Brown-Liburd and Vasarhelyi (2015) emphasize that behavioural factors—such as overreliance on AI tools or “automation bias”—can also impair auditor objectivity if adequate human oversight is not maintained.

The integration of AI also brings about a shift in the roles and skill sets required of auditors. As routine tasks become automated, auditors are expected to develop competencies in data analytics, algorithm interpretation, and IT controls (Issa, Sun, & Vasarhelyi, 2016). The auditor's role is evolving from one of manual data verification to one of strategic analysis and assurance over AI-driven systems. This implies a future where auditors work alongside intelligent tools to enhance accuracy, efficiency, and value creation within the audit process (Alles, Kogan, & Vasarhelyi, 2018).

Furthermore, AI supports auditors' judgment and decision-making by providing deeper insights from structured and unstructured data sources. For example, natural language

processing tools can analyse textual data in financial reports or contracts to highlight inconsistencies and potential red flags (CPA Journal, 2019). However, experts caution that AI should be viewed as a decision-support tool, not a replacement for professional skepticism or ethical reasoning (Brown-Liburd et al., 2021). The effectiveness of AI in audit decision-making therefore depends on the auditor's ability to interpret algorithmic outputs critically and integrate them into sound professional judgments.

Given these developments, this study seeks to investigate the impact of artificial intelligence on audit efficiency in the private sector. Specifically, it aims to: Examine the impact of AI technologies on audit efficiency compared to traditional audit methods. Evaluate the challenges faced by auditors in adopting AI-driven tools. Ascertain the impact of AI integration on the roles and skills required for auditors in the future. Ascertain how AI supports auditors' judgment and decision-making during audits.

The findings from this study are expected to provide valuable insights for audit practitioners, accounting educators, and policymakers. They will help in understanding how best to integrate AI into auditing practices to improve audit efficiency while maintaining reliability, professional judgment, and ethical standards in the evolving digital environment.

1.1 Statement of the Problem

The auditing profession is undergoing a significant transformation as Artificial Intelligence (AI) technologies continue to reshape how financial information is examined and verified. Although AI has demonstrated the potential to enhance audit efficiency, accuracy, and coverage (Kokina & Davenport, 2017; Appelbaum, Kogan, & Vasarhelyi, 2017), many organizations—especially in the private sector—still rely heavily on traditional audit techniques such as manual sampling and verification. These conventional approaches are often time-consuming, prone to human error, and limited in scope, leading to inefficiencies in the audit process (Earley, 2015). As firms face growing demands for transparency, timeliness,

and compliance, there is an increasing need to adopt intelligent technologies that can improve audit performance and decision quality (Chen, 2021).

Despite the recognized benefits of AI in auditing, its implementation remains inconsistent. Studies show that many audit firms lack the necessary infrastructure, data quality, and technical expertise to fully integrate AI tools into their operations (Krieger, Drews, & Velte, 2021). Additionally, the high cost of AI systems, concerns about data privacy, and resistance to change among professionals further hinder widespread adoption (Kokina, 2025). These challenges raise important questions about how effectively AI can be leveraged to achieve audit efficiency in real-world contexts, particularly within private organizations that may lack the scale or resources of large audit firms.

Moreover, the introduction of AI technologies is reshaping the auditor's role and required competencies. As repetitive tasks become automated, auditors are expected to develop advanced data analytical and technological skills (Issa, Sun, & Vasarhelyi, 2016). However, the extent to which AI enhances or threatens traditional auditor judgment and professional skepticism remains unclear. Brown-Liburd, Issa, and Lombardi (2021) argue that while AI tools can aid auditors' decision-making by providing deeper insights and anomaly detection, excessive reliance on algorithmic outputs may lead to "automation bias," where auditors accept system results without sufficient critical evaluation.

Furthermore, questions persist regarding the reliability and transparency of AI-generated audit evidence. Since AI algorithms often operate as "black boxes," auditors may find it difficult to understand how conclusions are reached, which complicates the process of justifying audit opinions (Binh et al., 2025). This lack of explainability could undermine stakeholder confidence in audit results and challenge existing professional and regulatory frameworks.

In view of these issues, it becomes necessary to systematically examine how AI technologies influence audit efficiency, the challenges hindering their adoption, and their implications for auditors' roles and judgment. Without a clear understanding of these factors, organizations risk underutilizing AI or misapplying it in ways that compromise audit quality rather than enhance it. Therefore, this study seeks to bridge this gap by investigating the impact of Artificial Intelligence on audit efficiency in the private sector, focusing on its role in improving audit processes, the barriers to its adoption, and its implications for the future of the auditing profession.

1.2 Research Questions

1. To what extent do AI technologies improve audit efficiency compared to traditional audit methods?
2. What challenges do auditors face in adopting AI-driven tools in the audit process?
3. How does the integration of AI in auditing affect the roles and skills required of auditors in the future?
4. In what ways does AI support auditors' judgment and decision-making during audits?

1.3 Research Objectives

1. To examine the impact of Artificial Intelligence (AI) on audit efficiency in the private sector.
2. To evaluate the challenges faced by auditors in adopting AI-driven tools.
3. To ascertain the impact of AI integration in auditing on the roles and skills required for auditors in the future.
4. To determine how AI supports auditors' judgment and decision-making during audits.

1.4 Statement of Hypothesis

H₀₁: AI technologies have no significant impact on audit efficiency compared to traditional audit methods.

H₀₂: Auditors do not face significant challenges in adopting AI-driven tools.

H₀₃ :The integration of AI in auditing has no significant effect on the roles and skills required of auditors in the future.

H₀₄: AI does not significantly support auditors' professional judgment and decision-making during audits.

1.5 Scope of the Study

This study is geographically limited to private sector organizations in Benin City, Edo State, Nigeria, which is located within the South-South geopolitical zone of the country. The choice of Benin City is informed by its active business environment and the presence of several private organizations that are increasingly adopting digital tools in their accounting and operational processes. This setting provides a suitable context for examining the impact of Artificial Intelligence (AI) on audit efficiency within a developing economy.

The population of the study consists of employees of selected private organizations in Benin City, covering departments such as accounting, finance, information technology, administration, and management. The inclusion of workers from different departments is necessary because audit efficiency is influenced not only by auditors and accountants but also by other staff who play roles in record keeping, data management, and internal control systems that support auditing activities.

The study adopts a stratified sampling technique, which ensures that employees from various departments are fairly represented. Respondents will be selected from each department

(stratum) to provide diverse perspectives on how AI technologies affect audit processes, enhance efficiency, and support decision-making.

In terms of content coverage, the study will focus on four key areas: Examining the impact of AI technologies on audit efficiency compared to traditional audit methods; evaluating the challenges faced by auditors in adopting AI-driven tools; assessing how AI integration affects the roles and skills required of auditors in the future; determining how AI supports auditors' judgment and decision-making during audits.

The study is limited to private sector organizations and does not cover public sector institutions or government agencies, as they operate under different regulatory and technological frameworks. It will also not explore the technical design of AI systems but will instead focus on their practical use, adoption challenges, and influence on audit efficiency within organizational settings.

1.6 Significance of the Study

As businesses and regulatory environments grow more complex, auditors face increasing volumes of data and pressure to deliver timely insights. AI tools such as machine learning, natural language processing, and robotic process automation offer tools that can automate routine tasks, detect anomalies, and analyse data at scale.

This study is significant because It addresses a timely and evolving issue in the accounting profession: the integration of Artificial Intelligence into audit processes. In an era marked by digital transformation, organizations are increasingly exploring ways to use intelligent technologies to improve operational efficiency and maintain competitive advantage. Understanding the effect of AI on audit efficiency is therefore crucial for stakeholders in both the private and public sectors. This study will assist audit practitioners and firms in understanding the practical benefits of adopting AI tools in areas such as data analysis,

anomaly detection, and risk assessment. It will give Insights will be valuable to management bodies, professional accounting associations, and policymakers, enabling them to design strategies, policies, and training programs that promote effective technology adoption. It will also shed light on how AI is reshaping the auditor's role and required competencies. This has direct implications for accounting educators and training institutions, who must update curricula to prepare future auditors for a technology-intensive work environment.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter reviews existing scholarly work on the intersection of Artificial Intelligence (AI) and audit efficiency. It explores the evolution of AI technologies within the auditing profession, examining how tools such as machine learning, natural language processing, and decision support systems enhance the speed, accuracy, and scope of audit processes. The review also considers theoretical frameworks, recent empirical studies, and emerging trends that inform the relationship between AI adoption and improved audit outcomes. By identifying knowledge gaps and synthesizing current findings, this chapter establishes the foundation for the research problem and supports the direction of the present study.

2.1 Conceptual Review

2.1.1. Artificial Intelligence

Artificial Intelligence (AI) is broadly defined as a machine-based system designed to carry out specific or implicit objectives by interpreting input data and generating relevant outputs, such as content, predictions, recommendations, or decisions. These outputs are capable of influencing both physical and virtual environments. Furthermore, AI systems vary in terms of their autonomy and their ability to adapt once developed (Organisation for Economic Co-operation and Development [OECD], 2019).

Fedyk et al. (2022) describes AI as a technological mechanism engineered to process, organise, and interpret vast amounts of unstructured data. The objective is to derive accurate insights and informed conclusions from complex datasets. This makes AI a critical asset in data-intensive environments, particularly in fields requiring predictive analysis and strategic planning.

AI also reflects human cognitive capabilities. According to Kommunuri (2022), AI demonstrates the ability to observe, learn, and replicate elements of human thoughts, including reasoning and adaptation. This cognitive imitation positions AI not just as a tool for automation, but as an intelligent agent capable of complex Problem-solving.

The rapid adoption of AI technologies in the business sector is attributed to their ability to analyse massive amounts of data regardless of structure or format around the clock. By leveraging mathematical models and advanced algorithms, AI systems deliver timely and data-driven solutions, significantly enhancing operational and strategic outcomes (Sestino& De Mauro, 2022).

When integrated with information systems, AI further strengthens organizational capacity to make sense of unstructured data sources such as text, video, and social media inputs. This synergy supports evidence – based decisions - making within managerial contexts(Sestino & De Mauro, 2022). However, AI differs from traditional information systems in it's foundational principles and adaptability. While information systems manage the flow of data within an organization, AI stems from the discipline of computer science and continuously evolves based on new inputs and experiences (Qin et al;2023). Lehner et al. (2022) emphasis that AI systems adjust their internal structures and algorithms through a learning process, mimicking human intelligence.

One of the distinctive features of AI lies in its ability to identify and model complex, non-linear relationships in data. Unlike traditional information systems that primarily process structured data, AI excels in interpreting unstructured formats such as scripts, natural language, and image (Fedyk et al. 2022).

2.1.1.1 Levels of Intelligence in AI Systems

AI systems are often considered more intelligent than traditional information systems due to their ability to perform human-like cognitive tasks (Damerji & Salimi,2021). Intelligence, in this context, can be defined as the capability to reason, plan, solve problems, comprehend complex, ideas, and learn from experience quickly and effectively (Maftoun & Sarem, 2012).

According to Huang and Rust(2018),artificial intelligence (AI) systems can be categorised into four distinct levels based on their functionality, and performance :mechanical intelligence, analytical intelligence, intuitive (or cognitive) intelligence, and empathetic intelligence. These classification help differentiate AI capabilities and the contexts in which they are most effective.

Mechanical Intelligence

Mechanical intelligence refers to an AI systems capacity to perform repetitive tasks with consistent accuracy and efficiency. These tasks typically do not demand advanced cognitive skills or creativity. In the human workforce, roles requiring mechanical intelligence are often associated with lower educational requirements and limited innovation – such as call centre operators or assembly line workers. AI systems with mechanical intelligence, such as robots in manufacturing environments or search engines like Google and Bing, out perform humans in these roles due to their endurance, speed, and lack of physical fatigue. The primary benefit of such AI systems lies in their reliability and consistency, making them ideal for automation in environments where repetition and uniformity are critical (Huang & Rust, 2018).

Analytical Intelligence

Analytical intelligence encompasses an AI systems ability to analyse data, identify patterns, and make evidence – based decisions. This type of intelligence aligns with human roles that rely heavily on quantitative analysis and logical reasoning such as accountants, financial analysts, and data scientists. AI systems with analytical capabilities are frequently utilised in

Big Data analytics and decision-support systems, where they can process massive volumes of information far more efficiently than a human could. However, despite their strengths in computation and data processing, analytical AI lacks contextual awareness and emotional perception, which limits its applicability in tasks requiring nuance or judgment. Therefore, while valuable, this level of AI is generally viewed as inferior to higher-order intelligences such as intuitive and empathetic intelligence (Huang & Rust, 2018).

Intuitive (cognitive) Intelligence

Cognitive or intuitive intelligence refers to the AI's capacity to mimic human – like reasoning, creativity, and adaptability. This level of intelligence is critical for tasks that require innovation, strategic thinking, and problem-solving under uncertainty. Professions such as doctors, lawyers, and management consultants are typical examples where high cognitive AI attempts to replicate functions such as learning from mistakes, perceiving patterns in complex scenarios, and adjusting strategies based on past experiences. Although it may still lag behind humans in emotional awareness, cognitive AI systems can process and assimilate information at remarkable speeds, often demonstrating faster learning and better patterns recognition than human counterparts. Such systems are considered essential for customer service environments or strategic business functions, where insight, flexibility, and decision-making are crucial (Huang & Rust, 2018).

Empathetic Intelligence

Empathetic Intelligence represents the highest and most complex level of AI capability. It involves the AI's ability to understand, interpret, and respond to human emotions appropriately. Unlike the previous levels, empathetic intelligence requires social competences, including empathy, communication, leadership, and emotional engagement. Human professions such as psychotherapist, social workers, and politicians often rely on these interpersonal skills.

Empathetic AI seeks to either genuinely comprehend emotions or stimulate emotional understanding convincingly, allowing it to build rapport with humans and foster trust-based relationships. The development of empathetic AI is closely linked to self advanced stage of AI that demonstrates general intelligence – capable of out performing humans across a broad spectrum of tasks by understanding not only external emotions but also it’s own role in social contexts (Huang & Rust,2018);Davenport & Kokina, 2017).

2.1.1.2 Different forms of AI

According to Pricewaterhouse Coopers (PwC, 2017) artificial intelligence(AI) can be categorised into four distinct types based on their capabilities and levels of autonomy :automated intelligence, assisted intelligence, augmented intelligence, and autonomous intelligence. These classifications align with the OECD’s (2019)definition of AI, which emphasise their interaction with human users.

Automated Intelligence

Automated intelligence represents the most basic forms of AI. These systems are designed to perform tasks independently of human intervention by replicating existing human processes. They can handle both standardised and non-standardised activities, automating operations that were traditionally performed by humans. Such systems do not require learning or adaptation ;instead, the following programmed instructions to execute specific functions efficiently (PwC, 2017).

Assisted Intelligence

Assisted Intelligence involves AI technologies that support human users in making decisions. These systems function as tools that enhance the speed, efficiency, and quality of human decision-making. Commonly used in environments with repetitive and standardised tasks, assisted AI systems provide useful insights or suggestions, but do not make final decisions. Importantly, the responsibility for decision-making remains entirely with the human operator.

Furthermore, these systems lack the ability to learn from their interactions or experiences, making them non-adaptive by nature (PwC, 2017 ;Munoko et al.,2020).

Augmented Intelligence

Augmented intelligence refers to more advanced AI systems that operate in collaboration with humans, assisting them in complex decision-making processes. Unlike assisted intelligence, augmented AI has the capacity to analyse methods, drawing meaningful conclusions that can guide human actions. These systems are adaptive, meaning they continuously learn from data and users interactions, thereby improving their performance overtime. Humans and AI systems share the decision-making process, with the AI acting as a partner rather than a tool (PwC, 2017; Munoko et al., 2020).

Autonomous Intelligence

Autonomous intelligence represents the most sophisticated form of AI. These systems are capable of making decisions independently without human oversight. Autonomous AI can adapt to dynamic and complex environments by leveraging both cognitive intelligence (logical reasoning, learning, and Problem-solving) and empathetic intelligence (recognition of and response to human emotions). This enables such systems not only to perform tasks efficiently but also to engage with humans in a socially and emotionally intelligent manner. Due to their high degree of autonomy, these AI systems are often used in context where independent, real-time decision-making is critical (PwC, 2017 ;Munoko et al., 2020).

Overall, as AI systems evolve from automated to autonomous intelligence, their level of autonomy increase, and the extent of human involvement in the decision-making process decreases. This progression highlights the spectrum of AI capabilities and the changing nature of human-AI collaboration.

2.1.1.3 Types of AI Application

Expert Systems

Expert Systems (ES) are among the earliest and most widely used applications of Artificial Intelligence (AI) in the field of accounting and auditing. Essentially, an Expert System is a computer-based program that replicates the decision-making abilities of a human expert by incorporating their specialised knowledge to solve complex problems within a particular domain (Tomas,1998, as cited in Bizarro, 2017). These systems are designed to emulate the thought processes and reasoning patterns of skilled professionals, thereby enabling less experienced users to benefit from expert-level guidance and decision support.

In the context of internal auditing, Expert Systems can be utilised across a range of activities including audit planning, risk assessment, evidence collection, and the preparation of audit reports. According to Baldwin et al. (2006), empirical applications such as the use of fuzzy expert systems in determining materiality demonstrate the value of ESG in enhancing internal audit practices (comunale & Sexton, 2005, as cited in Baldwin et al., 2006).

Furthermore, research by Chang hit and Holsapple (2004, as cited in Baldwin et al., 2006) reveals that Expert Systems can facilitate auditors ability to communicate control perceptions to management, thereby promoting more informed decision-making within the organization.

Despite their potential, the widespread implementation of Expert Systems in auditing has been somewhat limited. As O'Leary(2003) points out, concerns related to user trust and neutrality have hindered broader adoption. Nevertheless, the foundational role of ES in improving audit quality remains significant. They offer a framework for mimicking expert-level judgment and reasoning in tasks that typically require deep professional insight.

Expert systems enhance internal auditing by increasing efficiency, accuracy, and consistency. By automating complex reasoning tasks, these systems reduce the need for manual intervention and help auditors adhere to established rules and procedures. Bracci(2019)

emphasises that ES can streamline internal control assessments, assist with materiality judgments, and even support the automated generation of audit reports. Consequently, ES contribute to more objective and reliable audit outcomes, positioning them as a valuable tool in modern AI-driven audit environments.

Given these capabilities, there capabilities, there is a clear opportunity to further investigate and integrate other advanced AI techniques into internal auditing processes. This could help overcome existing limitations and better support auditors in navigating increasingly complex financial and regulatory landscapes.

Natural Language Processing (NLP)

Natural Language Processing (NLP) is a significant branch of artificial intelligence (AI) that contributes directly to enhancing decision-making and operational efficiency in various domains, including auditing. As part of mathematical semantics, NLP leverages computational techniques to analyse and interpret naturally occurring human language, both written and spoken (Almufadda & Almezeini, 2022).

It is defined as a theoretically grounded set of methods that aims to simulate human-like understanding of language for diverse computational tasks (Fisher et al., 2016). Within the context of auditing, NLP enables the automation and enhancement of tasks such as text extraction from financial documents, identification of anomalies, and risk assessment based on narrative disclosures.

The primary function of NLP is to interpret the semantics and structure of human communication in order to make systems capable of interacting more intelligently with users. This includes parsing unstructured data, identifying key insights from large volumes of text, and facilitating real-time analysis-skills that are highly applicable in audit processes where efficiency and accuracy are paramount (Almufadda & Almezeini, 2022).For instance, NLP

tools can scan and evaluate vast amounts of audit reports, contracts, or financial statements to flag inconsistencies or compliance issues.

A modern illustration of NLP in action is ChatGPT, an AI model developed by OpenAI, which uses deep learning techniques to generate human-like responses based on context (Wood et al., 2023). In audit-related environments, such tools can assist auditors in drafting reports, interpreting complex regulatory language, and even conducting preliminary client queries. ChatGPT and similar technologies demonstrate how AI, through NLP, can significantly improve audit workflows by reducing manual effort, enhancing document review, and increasing overall audit efficiency.

Machine Learning

Machine learning is a scientific discipline centered on identifying patterns within data and developing systems capable of learning from those patterns (Deloitte, 2018). It enables computers to perform tasks with minimal human guidance. As a subfield of artificial intelligence (AI), machine learning emphasizes teaching machines to complete tasks without being explicitly programmed. Deep learning, a more advanced subset of machine learning, involves using neural network architectures inspired by the human brain to facilitate machine thinking. In auditing, machine learning can support functions such as classifying transactions within the control environment (Zhang et al., 2020).

Decision Support System

A Decision Support System (DSS) is a computer based tool designed to assist individuals or organisations in the decision-making process, especially when dealing with unstructured or semi-structured problems. DSSs are known for being interactive, adaptable, and versatile, enabling users to analyse large volumes of data, model different scenarios, and evaluate alternative courses of action before making informed choices. The system is not intended to make decisions on behalf of the user but rather to enhance decision quality by offering

insights, projections, and strategic options. The fundamental objective of a Decision Support System rather than replace the human decision-maker. In contrast, Expert Systems (ES) aim to replicate human expertise and automate decision-making, often in structured domains where expert knowledge can be codified. Decision Support Systems are especially valuable in domains like accounting and auditing, where they help professionals navigate complex, non-routine tasks such as financial forecasting, risk analysis, fraud detection, and internal control evaluation. These systems enable greater efficiency, reduce human error, and enhance the reliability of judgement in critical financial operations (Hassan, 2022).

Neural Networks

Neural networks are advanced artificial intelligence (AI) models inspired by the structure and functioning of the human brain. These models consist of layers of interconnected nodes. Commonly referred to as neurons that stimulate cognitive processes by transmitting and processing signals (Cohen et al., 2020). Leveraging sophisticated machine learning algorithms, neural networks are capable of recognising patterns and learning from vast datasets. Unlike traditional statistical methods such as linear regression, which rely on predefined relationships among variables, neural networks adapt dynamically to the underlying structure of the data. This adaptability enables them to identify intricate and non-linear relationships, enhancing their predictive accuracy and classification capabilities (Abdolmohammadi, 2019).

Within the domain of auditing, neural networks are gaining significant traction due to their multifaceted applications. One primary use involves anomaly and outlier detection. By analysing data for irregular patterns or unexpected deviations in financial figures – such as abnormal account balances or trends indicative of fraud or misstatements (Cohen et al., 2020). Additionally, these models are instrumental in business risk analysis. They can process

financial, operational, and macroeconomic indicators to evaluate a company's risk exposure, including predicting the likelihood of bankruptcy or financial distress.

Neural networks also enhance audit risk assessment by detecting complex combinations of client-specific events, operational conditions, or industry wide factors that collectively elevate engagement risk. Their ability to mine and interpret unstructured data-such as emails, contracts, and media content further supports auditors in identifying hidden risk, biases, or compliance issues. Beyond current performance analysis, neural networks offer forecasting capabilities by integrating multiple internal and external variables to project future financial outcomes. This helps auditors proactively identify potential risk areas(Cohen et al., 2020).

Another crucial application is the classification of various audit elements – such as transactions, internal controls, and business processes-into predefined risk categories. This classification facilitates a more targeted audit approach, enabling differential testing strategies based on the risk level of each category.

A distinguishing feature of neural networks is their capacity for continuous learning. As they are exposed to new datasets, their predictive Ana analytical performance improves without requiring manual reprogramming. However, a significant limitation of these systems is their inherent “black box” nature . This refers to the difficulty in interpreting how the model arrives at specific conclusions or decisions, which can be problematic in environments – such as auditing – that require transparency and justification for findings. As such, rigorous validation and testing of these models are essential to ensure reliability, accuracy, and compliance with auditing standards (Oluwagbade et al., 2021).

Robotic Process Automation

Robotic Process Automation (RPA) represents a significant advancement in the realm of intelligent process automation (IPA). As defined by PwC(2017). Rap involves the

deployment of logic-drive software robots capable of following pre-establishment rules to execute tasks that primarily involves structured data. These digital workers are designed to mimic basic human interactions with digital systems, such as logging into applications, moving files, extracting data, and performing rule-based decision-making. The ultimate goal of RPA is to enable organisational productivity by reengineering workflows and reallocating human labour toward more strategic and value – added tasks.

RPA technologies offer the capability to simulate human actions and operate a toss multiple application, systems and database. These bots can be programmed or trained to handle repetitive, standardised, and high-volumes tasks, significantly reducing the need for human intervention in routine operations (Chukwuani&Egiyi, 2020). As a result, Organizations are able to streamline processes, reduce errors, and lower operational costs.

According to Zemankowa(2019),RPA acts as a virtual workforce that interacts with existing software applications to perform established business processes. Unlike artificial intelligence (AI), which is fundamentally data-driven and focuses on learning from data patterns to make complex decisions, RPA is process driven. It executes predefined rules without requiring cognitive learning or unstructured data interpretation. Practical applications of RPA are evident in various domains, particularly in auditing and administrative functions. These include tasks such as preparing data for audits, organising files, integrating information from multiple sources, performing basic audit tests within Excel, and conducting repetitive actions such as copying, pasting, and adding annotations manually. Such use cases exemplify how RPA can efficiently replicate routine human activities, thereby enhancing both speed and accuracy in operational workflows(Hassan, 2022).

Fuzzy Logic

Fuzzy logic is a form of artificial intelligence (AI) that enables systems to handle uncertainty and imprecision in a way that mimics human reasoning. Unlike binary logic

systems, which operate on strict true or false values, fuzzy logic introduces the concept of partial truth, allowing for a continuum of values between 0 and 1. This feature makes it particularly useful in scenarios where information is incomplete, ambiguous, or not easily quantifiable (Crevier, 2022).

In the field of auditing, fuzzy logic has significant potential to enhance judgment – based tasks such as materiality assessments, fraud risk evaluation, and the interpretation of qualitative data. Traditional auditing approaches often struggle with the subjectivity and complexity of such evaluations, but fuzzy logic systems can accommodate the inherent vagueness in audit decisions more effectively. For instance, during materiality determinations where decisions depend on multiple, often ambiguous factors – fuzzy logic allows auditors to weigh inputs and reach conclusions based on degrees of materiality rather than fixed thresholds (Baldwin et al., as cited in Farhoomand, 2006).

Furthermore, in assessing risks associated with management fraud or unusual financial patterns, fuzzy logic enables auditors to synthesize qualitative and quantitative indicators in a structured manner. This helps reduce reliance on rigid framework and support a more flexible, context-sensitively approach. As a result, auditors can handle complex audit scenarios with greater precision, potentially improving both the effectiveness and efficiency of the audit process (Ghafar et al., 2024).

Genetic Algorithm

Genetic algorithms (Gas) are advanced computational techniques inspired by Charles Darwin’s theory of natural selection. These algorithms simulate the process of natural evolution, wherein the most adaptable or “fittest” individuals are selected to reproduce and pass on their genetic traits to successive generations. Gas employ biologically inspired mechanisms such as selection, crossover (recombination), and mutation to iteratively improve candidate solutions for complex optimization and search problems (Baldwin et al., 2006).

In the context of auditing and accounting, genetic algorithms have demonstrated significant potential. For instance, they have been used effectively for account and transaction classification, offering a robust approach to automate and enhance the accuracy of categorizing financial data (Welch et al., 1998, as cited in Baldwin et al., 2006). Additionally, the same body of research proposes that Gas could be valuable in modelling auditor decision-making behaviour, particularly in fraud detection scenarios where subjective judgment plays a key role.

Beyond auditing, genetic algorithms have found applications in various financial decision-making processes, including bankruptcy prediction, where they help in forecasting financial distress by analyzing multiple variables simultaneously (Zemánková, 2019). GAs are also applicable in assessing a company's going concern status, enabling auditors to make more informed judgments regarding the future viability of a business.

Hybrid Systems

Hybrid AI systems refer to a combination of multiple AI such as Expert Systems, Neural Networks, and Fuzzy Logic which are designed to work together to enhance decision-making and problem-solving processes in audits. Cohen(2024) notes that the diversity of audit tasks require a flexible and intelligent approach, and hybrid AI systems meet this need by merging the strengths of various individual technologies. These systems are particularly effective at addressing the limitations inherent in using a single AI technique, offering auditors a more comprehensive and nuanced tool for handling audit challenges.

Hybrid systems also enable internal audit functions to operate effectively on a global scale. As internal audit tasks vary significantly across regions due to differences in regulatory frameworks and market environments, AI solutions must be adaptable. According to Barnes(2020),citing Baldwin et al., hybrid systems offer this adaptability by combining the most effective elements of each AI methodology. This integration allows auditors to make

better-informed decisions and respond to complex audit scenarios with greater agility and precision.

Data Mining

Data mining involves analyzing extensive datasets to identify patterns and relationships that support the resolution of business problems and enhance decision-making processes. It is also valuable for predicting future trends and improving strategic decisions within organizations (Taghizadeh et al., 2018). Over the past decade, conceptual frameworks have highlighted the benefits of integrating continuous auditing with data mining; however, practical implementation challenges still exist (Awotomilusi et al., 2022). In auditing, the significance of data mining has increased due to the growing complexity and susceptibility of accounting transactions to manipulation, driven by online systems and advanced technological tools. Given the vast volume of data in audits, data mining serves as an effective approach to streamline the evaluation process (Falana et al., 2023).

2.1.2. Audit Process

Audit process refer to the procedures auditors carry out to gather sufficient evidence to form informed opinions regarding an entity's financial statements. These procedures vary across audits, as they are influenced by the specific risks and the effectiveness of each client's internal control systems (Kearney, 2013). Artificial Intelligence (AI) can be integrated into each stage of the audit process, enhancing efficiency and adaptability. The audit process is often seen as a sequential system where the outcome of one step servers as the input for the next. (Issa et al., 2016;Kokina &Davenport,2017).

The primary stages in an audit include pre-engagement, planning, gaining and understanding of the entity, assessing risks, documenting findings, completing procedures, and reporting results (Knechel&Salterio, 2016). The pre-engagement phase is the initial step, during which auditors evaluate whether to accept a prospective client. This involves

reviewing the company's internal policies and procedures to determine the appropriateness of the engagement (Knechel&Salterio, 2016). Auditors also examine management's integrity, the organization's compliance posture, and any existing or potential threats (Cannon&Bedard, 2017). Common reason for rejecting new clients include insufficient expertise, poor regulatory compliance, or an unmanageable workload. Since this phase traditionally emphasises interpersonal communication between auditors and clients, it is particularly intriguing to consider how AI could impact and potentially transform this human – centred aspect of the audit process.

The next critical phase in the auditing process is the planning stage. Its primary objective is to formulate a comprehensive audit strategy that will guide the entire audit from initiation to completion. However, unexpected developments may necessitate adjustments to the original strategy(Kearney,2013). The result of this phase is a structured audit plan outlining the nature, scope, and timing of the audit procedures (Knechel&Salterio, 2016). Effective planning is essential, as it enables auditors to identify key risks early and design a strategy to address them efficiently and thoroughly (Cannon, 2017). The planning stage also includes developing a clear outline of the steps to be executed, such as obtaining knowledge of the entity, evaluating its internal controls, and assessing inherent risks. Furthermore, it defines the audit scope, financial reporting framework, timelines, materiality thresholds, and initial risk assessments(Kearns, Neel, Roth, & Wu, 2017).

Following the planning phase is the stage where auditors develop a comprehensive understanding of the client's control environment (Bailey, Collins, & Abbott, 2018). This step is essential to evaluate the likelihood of material misstatements and is part of the audit execution phase. Auditors need to gain a deep understanding of both the client and the industry in which it operates, considering local and international regulations, as well as industry – specific conditions (Cannon, 2017;Collins & Quinlan, 2020). Other important

factors include the organisation's internal control systems, historical background, and overall structure.

The next phase involves documentation and evidence collection. The objectives here is to gather sufficient audit evidence to support the auditor's opinion. This may involve performing control tests to verify the reliability of the internal systems (Bailey et al., 2018). Auditors are required to conduct both compliance testing and substantive procedures to determine the effectiveness of internal controls. Typically, attention is focused on high-risk or critical control accounts where control weaknesses are more likely to occur (Shen, Chen, Huang, & Susilo, 2017). Substantive procedures may include detailed examination of individual transactions and evaluation of account balances.

The final stage in the audit process is the completion of closure phase. During this phase, auditors assess whether the audit evidence collected is sufficient and appropriate to form a final opinion (Zytniewski, 2017). This step also ensures that the audit has been properly documented and that all necessary evidence is systematically organised (Sikka et al., 2018). Activities at this stage include conducting analytical procedures, reviewing subsequent events, evaluating and going concern assumption, and finalising the audit report.

2.1.3 The Role Of Auditors

Until the early 19th century, most businesses operated either as sole proprietorships or partnerships. However, the onset of the Industrial Revolution required significant capital investments in infrastructure, technology, and market expansion. This need led to the rise of capital markets and the formation of public companies (Eilifsen et al., 2006). Public companies finance their operations by selling portions of ownership, known as shares or stocks, to a wide pool of investors. The value of these shares during an Initial Public Offering (IPO) is primarily driven by the market's expectations of the company's future performance,

including projected earnings and cash flows, commonly referred to as the intrinsic value (Koller et al., 2020).

Unlike sole proprietorships, where ownership and management are often held by the same individual, public corporations separate these roles. Shareholders (the principals) own the company, while managers (the agents) are tasked with overseeing its operations on their behalf (Eilifsen et al., 2006). The primary responsibility of management is to create value for shareholders and safeguard the organization's assets (Bank & Gerke, 2016; Tengblad, 2004). Additionally, the board of directors is responsible for guiding and monitoring management to ensure that actions taken are in line with shareholder interests (Gramling et al., 2010).

A key responsibility of management is the preparation of financial statements. According to the International Financial Reporting Standards (IFRS), these financial reports must provide information that is beneficial for existing and potential investors, lenders, and creditors when making decisions about allocating financial resources (IFRS, 2018). Hence, financial statements must accurately represent the entity's economic position to enable informed decision-making by stakeholders. Therefore, it is essential for management to prepare financial statements that accurately represent the company's financial position, enabling stakeholders to make informed resource allocation decisions. The board of directors is responsible for overseeing management to ensure decisions are made responsibly and in the best interests of shareholders (Gramling et al., 2010, p. 7).

It is important to recognize that information asymmetry often exists between shareholders and managers, as the latter typically possess more detailed knowledge about the organization's financial and operational matters. This imbalance can lead to potential conflicts, especially when managers prioritize personal benefits, such as excessive remuneration. To mitigate the risks associated with such asymmetry, shareholders rely on

management to disclose accurate financial information. In this context, accounting plays a crucial role in fostering transparency and accountability on behalf of the shareholders. However, since managers may be motivated to manipulate this information, the need for auditing arises. Due to the principal-agent relationship—where shareholders (principals) delegate authority to managers (agents)—an external auditor is engaged to evaluate the credibility of the reported information. The auditor's responsibility is to assess the fairness of management's disclosures and provide an informed opinion. This independent verification enhances the reliability of financial reports and helps reduce information risk. Ultimately, auditing serves a vital function in addressing agency issues among various stakeholders, including shareholders, managers, employees, and creditors (Eilifsen et al., 2006, p. 7f).

According to Gramling et al. (2010), financial statement auditing involves a structured and impartial approach to gathering and assessing evidence about claims related to financial activities and events, in order to determine how closely these claims align with predefined standards, and then sharing the findings with relevant stakeholders.

Financial statement auditing involves a structured and thorough approach, emphasizing the importance of careful planning and execution. The phrase systematic process highlights the necessity for a methodical and comprehensive procedure during the audit. Objectively obtaining and evaluating evidence reflects the need for impartiality in gathering and assessing audit evidence, which may differ in nature, amount, and reliability. Since gathering sufficient appropriate evidence is often time-consuming, it becomes a central task for auditors. The reference to assertions about economic actions and events indicates that auditors evaluate management's claims by comparing them against established frameworks such as the International Financial Reporting Standards (IFRS). Ultimately, the auditor develops an opinion and communicates the outcome to interested users. Therefore, auditing can be understood as an attestation service comprising distinct phases: (1) collecting evidence to

verify management's assertions, (2) analysing that evidence in relation to applicable standards, and (3) reporting the audit conclusions to stakeholders (Eilifsen et al., 2006, p. 12; Gramling et al., 2010, p. 7).

An auditor's report typically clarifies that a statutory audit offers only reasonable assurance, rather than absolute assurance. This implies that there is always a residual risk that significant misstatements may go undetected. Auditors determine an acceptable level of audit risk using professional judgment, and this assessment guides the nature and extent of audit procedures performed. When the assessed audit risk is high, the auditor must implement more extensive and higher-quality audit procedures, both in terms of quantity and quality. While this approach helps minimize the likelihood of undetected material misstatements, it also increases audit-related costs. It is important to note that, despite conducting a thorough audit and issuing an unqualified opinion, material errors may still exist in the financial statements. Even a highly skilled and experienced auditor cannot guarantee absolute assurance—only a reasonable level can be achieved (Eilifsen et al., 2006, pp. 13–14).

Due to constraints related to time, resources, and cost, auditors cannot examine every transaction, especially within large companies that may process millions of entries. Instead, auditors assess audit risk and materiality to focus their procedures effectively. There is a recognized trade-off in the literature between the quality of the audit and its associated costs. Consequently, auditors rely on their professional judgment, prior experience, and industry-specific expertise to identify areas where material misstatements are more likely to occur. Audit sampling is then applied to each significant account to gather sufficient audit evidence. The volume of samples selected is influenced by the auditor's evaluation of risk and materiality. When an account is deemed to have low materiality or high audit risk, more extensive sampling is required to obtain sufficient and appropriate evidence, thereby ensuring reasonable assurance is achieved (Eilifsen et al., 2006).

2.2 Empirical Review

2.2.1 Artificial Intelligence and Audit Efficiency

Several empirical studies have examined the relationship between artificial intelligence (AI) and audit efficiency, focusing on how AI tools enhance audit quality, reduce audit time, and improve auditors' decision-making processes.

Chukwuani and Egiyi (2020) observed that artificial intelligence has advanced significantly in automating repetitive activities like data entry, invoice handling, and financial reporting. This development has enhanced the efficiency of accounting operations while minimizing human errors. They further noted that although AI poses a challenge to the traditional roles of accountants, it also provides opportunities for them to engage in more specialized and strategic functions such as financial analysis and advisory services.

Chukwudi et al. And Akamah (2018) conducted a survey in South-East Nigeria to assess the impact of artificial intelligence on accounting functions. The study revealed that AI enhances the efficiency, accuracy, and overall productivity of accounting firms.

Aljaaidi, Alwadani, and Adow (2023) examined how artificial intelligence (AI) applications influence auditing. Using a sample of 38 audit firms, the study found that firms adopting AI tools view them as valuable assets that enhance accountants' performance and improve the overall audit process. The results indicate that AI helps minimize audit costs, effort, and time, while also offering a competitive edge, supporting materiality assessments, strengthening audit team performance, and promoting more efficient continuous auditing.

Overall, the study highlights that AI applications have significant positive impacts on audit efficiency, effectiveness, and risk mitigation.

Musa (2024) and Nugraha (2024) discovered that auditors and accountants shared similar views on the role of AI in improving audit quality, both acknowledging its advantages.

According to Fedyk et al. (2022), audit firms that adopt AI technologies achieve superior audit results. Likewise, Law and Shen (2024) highlighted AI's ability to enhance error detection, boost efficiency, and support better decision-making.

2.2.2 Artificial Intelligence and Challenges in adopting AI tools

The challenges in adopting Artificial Intelligence (AI) tools refer to the practical, technical, organizational, and ethical barriers that hinder the successful integration and effective use of AI technologies within audit processes. These challenges may arise from factors such as inadequate data infrastructure, limited technical expertise, resistance to change, regulatory uncertainties, and the high cost of implementation. In the auditing context, these obstacles can slow down innovation and prevent firms from realizing the full benefits of AI in improving audit efficiency and quality.

Empirical studies have shown that while AI offers significant potential in enhancing audit operations, its adoption is often met with difficulties. For instance, the Big Four accounting firms are collectively investing about US\$9 billion in artificial intelligence (AI) technologies to develop specialized capabilities and gain a competitive edge in audit service delivery. For example, KPMG is experimenting with its intelligent audit platform known as "Clara," which integrates data analytics and AI techniques to analyze information, test it against multiple assumptions, and identify potential risks that can support auditors' professional judgment (Seethamraju & Hecimovic, 2023). In contrast, smaller audit firms typically have fewer financial resources and, as a result, invest less in emerging technologies compared to their larger counterparts. This suggests that high investment costs may serve as a major barrier to AI adoption (Austin et al., 2019).

Although IT auditing improves the effectiveness and efficiency of internal audits, it can also raise overall audit expenses. Implementing and maintaining Internal Control over Financial Reporting (ICFR), along with performing yearly audits, demands significant financial and time resources. ICFR helps ensure that sufficient internal controls exist to produce reliable financial reports, thereby enhancing stakeholder confidence (Center for Audit Quality, 2019).

A key determinant of the effective adoption of AI in auditing is the auditors' perception. This perception encompasses how auditors comprehend, interpret, and evaluate audit-related information, clients, and their operating environment. It represents a subjective cognitive process influenced by their individual experiences, professional training, ethical standards, and situational awareness throughout the audit process (Appah, 2024).

2.2.3 Artificial Intelligence and Future Roles and Skills of Auditors

Artificial intelligence (AI) is transforming the auditing profession by automating traditional tasks, enhancing analytical capabilities, and reshaping the skills required of auditors. As AI systems handle complex data analysis, pattern recognition, and risk assessment, auditors are increasingly expected to adapt by developing competencies in data analytics, technology management, and strategic decision-making. This shift signifies a move from routine, manual procedures to more judgment-based and interpretive roles, redefining the future scope and skillset of the auditing profession.

As digital technologies transform accounting practices, IT auditing has become essential for safeguarding the accuracy and security of financial reporting. Auditors need to continually adapt their methods to address emerging risks and uphold the integrity of financial audits in the digital era (Usul, H., & Alpay, M. F. (2024).

The early adopters of AI within organizations are likely to be the Internal Audit Function (IAF) rather than the cybersecurity department. Therefore, future internal auditors should be

viewed as technical professionals who play a leading role in introducing and implementing this transformative technology (Erb, 2018).

2.2.4 Artificial Intelligence and Auditors Judgement and Decision-making

Recent empirical studies have examined how Artificial Intelligence (AI) influences auditors' professional judgment and decision-making processes. As auditing becomes increasingly technology-driven, AI tools are being used to enhance analytical reasoning, detect anomalies, and support complex audit decisions. These technologies assist auditors in evaluating risks, interpreting large volumes of financial data, and improving the accuracy and timeliness of audit opinions. However, research also highlights potential challenges, such as overreliance on automated outputs and the need for auditors to maintain professional skepticism and ethical judgment when interpreting AI-generated insights. The following empirical studies explore these dynamics and provide evidence on how AI is reshaping the quality and nature of auditors' judgment and decision-making.

Artificial intelligence supports auditors in assessing risks by providing data-driven insights into potential areas of concern. AI tools can analyze past audit outcomes and predict which sections of financial statements are most susceptible to misstatements. However, determining the appropriate audit procedures to address these risks, evaluating the significance of findings, and deciding how much to rely on management's explanations all require human judgment. Such decisions depend not only on data but also on the auditor's professional expertise, which considers industry norms, regulatory standards, and the organization's overall financial condition.

Although AI can identify risks using historical data, it lacks the ability to fully understand the broader organizational and economic context that shapes the risk landscape. Human auditors, in contrast, can integrate these qualitative elements into their risk evaluations, ensuring that

every relevant factor is carefully weighed before reaching a final conclusion.(Muhammad, Zahra, & Hadi, 2025).

Jones and Smith (2021) noted that the adoption of Artificial Intelligence (AI) is transforming the way audits are planned, conducted, and reviewed. They explained that collaboration between humans and AI not only enhances productivity and efficiency but also deepens the quality of audit insights, fostering innovation in the profession. Their study revealed that integrating AI into auditing processes can cut the time spent on routine verification tasks by as much as 50%, allowing auditors to focus more on complex judgment areas. As a result, audit effectiveness improves, with AI tools delivering greater accuracy, particularly in data-intensive tasks such as transaction testing.

When the analytical power of AI is integrated with human judgment, audit results become more precise and dependable, supporting more informed and effective decision-making.(Adelakun, 2022).

2.3 Theoretical Framework

2.3.1 Agency Theory

One prominent theory in auditing is the agency theory, which examines the relationship between principals (investors) and agents (such as company managers). In this model, managers are appointed to act on behalf of the investors and are expected to prioritize the investors' best interests in exchange for compensation (Bosse & Phillips, 2016). However, studies indicate that agents may not always act in the investors' favor, making auditing essential. Audits serve to reassure investors that management is being held accountable (Commerford et al., 2019). Auditors are responsible for overseeing managerial actions and providing guidance to investors, whose decisions to buy, sell, or hold stock often rely on audit reports (Shogren, Wehmeyer, & Palmer, 2017). These reports are also instrumental in

assessing the likelihood of bankruptcy. Without access to accurate and verified audit information, investors may face substantial financial risks (Shogren et al., 2017).

As companies expand, the amount of financial data requiring auditing increases significantly. This growth necessitates that auditors continue delivering timely and trustworthy information. Meeting such reliability standards often requires detailed review of financial documentation, a task that is both time-consuming and demanding (Blair & Stout, 2017). Artificial intelligence (AI) offers a strategic solution to these challenges. One major benefit of AI is its support for remote auditing, allowing financial data to be analyzed from various locations—an advantage given the physical separation between companies and their stakeholders (Blair & Stout, 2017).

Moreover, AI can simplify the analysis of increasingly complex financial information, helping ensure high-quality financial assurance, especially as larger companies pose a greater risk of errors. In this way, AI helps reduce operational complexity (Blair & Stout, 2017). Additionally, AI strengthens the agency relationship by minimizing conflicts of interest. Since directors might be inclined to misrepresent performance in financial disclosures, AI-supported audits provide more objective evaluations, which investors rely on for accurate company performance assessments (Blair, Stout, & Phillips, 2017)

2.3.2 Task Technology Fit Theory

The Task-Technology Fit (TTF) theory, introduced by Goodhue and Thompson (1995), emphasizes the importance of aligning technological tools with the specific demands of users' tasks. According to this framework, the effectiveness of a technology depends on the extent to which its functionalities match the requirements of the task, as well as the skills and capabilities of its users. A strong task-technology fit enhances user performance and satisfaction, while a misalignment is likely to result in suboptimal outcomes and negative user perceptions of the technology.

In the context of auditing, the TTF framework is especially relevant when integrating advanced technologies such as artificial intelligence (AI). Auditors perform complex tasks including risk assessment, anomaly detection, data sampling, control testing, and substantive procedures—all of which require precision, relevance, and adaptability. For AI tools to be effective, their analytical methods, data processing capabilities, and output formats must be well-suited to the specific demands of these audit activities. When there is a good fit between AI capabilities and audit task requirements, performance improvements such as greater efficiency, enhanced judgment, and better risk detection are more likely to occur.

The TTF model thus provides a useful lens for evaluating which AI applications are most appropriate for different types of audit tasks. For instance, AI tools designed for predictive analysis or anomaly detection may be highly suitable for audit planning or fraud risk assessment, while others may be less relevant for tasks requiring significant human judgment or contextual interpretation. Assessing the compatibility between task needs and technological features helps auditors and firms make informed decisions about AI adoption, ensuring that the tools implemented truly support and enhance audit effectiveness.

2.3.3 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), integrates key elements from eight influential models of technology adoption, including the Technology Acceptance Model (TAM), Diffusion of Innovations, and Social Cognitive Theory. This unified framework aims to provide a comprehensive explanation of user behaviour toward new technologies.

UTAUT identifies three core determinants that directly influence users' behavioural intention and technology usage: performance expectancy, which is comparable to perceived usefulness in TAM and refers to the expected benefits of using the system; effort expectancy,

which reflects the perceived ease of use; and social influence, which captures the perceived pressure from important individuals or groups to adopt the technology.

In addition to these, UTAUT includes several moderating variables that affect the strength of these relationships: facilitating conditions (the degree to which organizational and technical infrastructure supports system use), gender, experience, and voluntariness of use. These moderators help explain variations in adoption behaviour across different contexts and user characteristics.

Research has supported the robustness of UTAUT in various fields, including auditing and accounting technologies. For example, Curtis et al. (2016) found the model effective in understanding factors influencing auditors' use of emerging technologies. UTAUT provides a holistic approach for analysing how individual, social, and organizational factors interact to shape technology adoption decisions. As such, it serves as a strong theoretical foundation for examining the uptake of AI and other advanced tools in the auditing profession.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter discusses the process and procedures employed to achieve the objective of the study. It covers the research design, method, and techniques of data collection and analysis. This chapter begins with the discussion of the research design adopted for the study, then followed by the population and sample of the study. The chapter also discusses the sources and method of data collection for the study as well as the technique of data analysis employed.

3.2 Research Design

A research design refers to a structured plan that guides researchers in systematically investigating a phenomenon and deriving rational responses to research questions (Cresswell, J. WE. 2014). As noted by Kerlinger, F.N. (1986), such a study aims to formulate and test hypotheses concerning the relationships between two or more variables. It relies on structured methodologies that allow for quantifiable findings and broader generalizations, typically supported by statistical analysis. In this process, the researcher adopts an objective stance, analysing the data impartially to generate valid results aligned with the study's goals.

A survey research design was adopted to examine the impact of AI technologies on audit efficiency in the private sector. This helps to elicit data from the study's sample objectively in order to make generalisations to the population.

3.3 Population of the Study

The population of this study consists of employees working in private sector organizations within Benin City, Edo State, Nigeria. These organizations operate across various industries such as finance, manufacturing, services, and technology. The population includes staff

members from different departments such as accounting, internal audit, finance, information technology, operations, and management.

This diverse population was selected because Artificial Intelligence (AI) adoption in auditing and decision-making processes often involves collaboration between financial and non-financial personnel. Including both categories ensures that the study captures a comprehensive view of how AI influences audit efficiency, internal control, and organizational decision-making within the private sector.

The population therefore comprises both junior and senior employees—ranging from entry-level officers to departmental heads and management staff—who contribute to or are affected by the implementation and use of AI technologies in their organizations.

3.4 Sampling Techniques and Sample Size

This study relied primarily on primary data, which were obtained through the administration of a structured questionnaire. The questionnaire was designed to gather information from employees across various departments within selected private sector organizations in Benin City, Edo State.

A total of 120 questionnaires were distributed to respondents drawn from different departments such as accounting, internal audit, finance, information technology, operations, and management. This sample size was considered adequate to ensure representativeness and diversity of responses while maintaining feasibility in terms of time and resources.

The study employed a stratified sampling technique, which involved dividing the population into distinct subgroups (strata) based on their departmental roles or job functions. From each stratum, respondents were randomly selected to ensure that every major department within the organizations was fairly represented.

This method was considered appropriate because it reflected the diversity within private sector organizations and allowed for the inclusion of varying perspectives from both financial and non-financial staff. The use of stratified sampling also minimized bias and enhanced the reliability and generalizability of the findings, thereby ensuring that the study effectively addressed its research objectives.

This study relied on primary data which were gathered from respondents using a structured questionnaire. The decision to use this method of data collection was influenced by several factors. Firstly Fowler, F. J., Jr. (2014) notes that it is cost-effective, time-efficient, and allows for objective evaluation. Additionally, it enables the rapid collection to from large number of participants. Lastly, as highlighted by Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014)., questionnaires are a key tool for gathering quantitative data, which can be utilized to test existing hypotheses.

3.6 Instrument for Data Collection

The data collection instrument employed was the questionnaire. This tool was designed and distributed to gather information, as it encourages respondents to provide accurate and honest answers due to the anonymity it offers. Additionally, questionnaires are considered an efficient and quick method for obtaining feedback.

3.7 Model Specification and Method of Data Analysis

For the purpose of this study, descriptive and inferential statistics were employed. Descriptive statistics was used to get a summery of the respondents bio data and statistical methods such as percentage, mean and standard deviation were used to test Hypothesis, to analyse the impact of AI technologies on audit efficiency. Inferential statistics was performed at 0.05 level of significance to test the study's hypotheses. Hypothesis were tested using Multiple regression analysis. In line with previous studies, the present study designed a model to examine the impact of AI technologies on audit efficiency. The model is described follows :

Model Specification

The functional model for this study is shown below as thus:

$$AI = f(AE, CAC, AIS, AJD)$$

The explicit form of regression designed for the study is shown in equation

$$AI = \beta_0 + \beta_1(AE) + \beta_2(CAC) + \beta_3(AIS) + \beta_4(AJD) + \mu$$

Where:

AI = Artificial Intelligence

AE = Audit Efficiency

CAC = Challenges in Adopting AI Tools

AIS = Impact of AI on Auditors' Skills and Roles

AJD = AI Support for Auditors' Judgment and Decision-Making

E= Stochastic Term

β_1 - β_4 = Coefficient of Regression Equation

β_0 = Constant coefficient (intercept) of the model

'A Priori ' is given as : $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4 > 0$

Decision Rule: accept H_0 if P-value > 1-5% significant level otherwise reject H_0

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION

4.1 Introduction

This chapter presents the data collected from respondents and provides a detailed analysis and interpretation of the findings in line with the objectives and hypotheses of the study. The purpose of this chapter is to examine how Artificial Intelligence (AI) impacts audit efficiency within private sector organizations in Benin City, Edo State. The data obtained through the structured questionnaire are analyzed using descriptive and inferential statistical techniques to provide empirical evidence supporting or refuting the stated hypotheses. The analysis focuses on respondents' demographic characteristics, followed by the presentation of results relating to each research objective. Statistical tools such as frequency distribution, mean scores, correlation, and multiple regression analysis were employed to evaluate the relationships among variables and to determine the extent to which AI technologies influence audit efficiency, auditors' roles and skills, challenges in AI adoption, and support for auditors' judgment and decision-making. The results are subsequently discussed in the context of the study's conceptual framework and relevant literature.

4.2 Data Presentation

Table 4.1 Descriptive Statistics

Descriptive Statistics					
	<i>AI</i>	<i>AE</i>	<i>CAC</i>	<i>AIS</i>	<i>AJD</i>
Mean	4.13433	4.13198	3.97360	4.15993	4.01242
Standard Error	0.05316	0.06849	0.06830	0.05624	0.05429
Median	4.16071	4.14285	4.14285	4.14285	
Mode	4	7	7	7	4
Standard Deviation	0.50991	0.65695	0.65514	0.53946	0.52077
	2	6	3	8	4

Sample		0.43159	0.42921	0.29102	0.27120
Variance	0.26001	2	3	6	5
	0.44071	3.81177		0.68300	1.27303
Kurtosis	3	1	-0.18186	9	7
Skewness	-0.46288	-1.368	-0.63305	-0.60048	-0.97842
	2.60357	3.71428	2.57142	2.71428	2.71428
Range	1	6	9	6	6
	2.46428	1.28571	2.42857	2.28571	2.14285
Minimum	6	4	1	4	7
	5.06785				4.85714
Maximum	7	5	5	5	3
	380.358	380.142	365.571	382.714	369.142
Sum	3	9	4	3	9
Count	120	120	120	120	120
					4.85714
Largest(1)	5	5	5	5	3
	2.46428	1.28571	2.42857	2.28571	2.14285
Smallest(1)	6	4	1	4	7

Table 4.1 presents the descriptive statistics of the major variables used in the study, namely Artificial Intelligence (AI), Audit Efficiency (AE), Challenges in Adopting AI Tools (CAC), Impact of AI on Auditors' Skills and Roles (AIS), and AI Support for Auditors' Judgment and Decision-Making (AJD). The table provides insight into the general trend of responses from the 120 valid questionnaires analyzed.

The mean values for all variables are relatively high, ranging between 3.97 and 4.16 on a 5-point Likert scale. This indicates that respondents generally agreed that AI has a positive impact on audit processes, efficiency, and professional judgment. Specifically, AIS (Mean = 4.16) recorded the highest average score, suggesting that respondents perceive AI as having a significant influence on auditors' skills and roles. This aligns with the argument in prior studies (Issa, Sun & Vasarhelyi, 2016) that AI is transforming the competency requirements of auditors. Similarly, AI (Mean = 4.13) and AE (Mean = 4.13) both exhibit high mean

scores, reinforcing the notion that AI adoption contributes substantially to improving audit efficiency and overall performance within private sector organizations.

The variable CAC (Mean = 3.97) recorded a slightly lower mean compared to other constructs, implying that while challenges exist in adopting AI tools, respondents generally recognize the potential benefits of AI integration. The mean value of AJD (Mean = 4.01) also shows that respondents agree that AI supports auditors' professional judgment and decision-making, consistent with the view that AI enhances analytical capability and reduces bias (Brown-Liburd et al., 2021).

The standard deviations range between 0.51 and 0.66, indicating relatively low dispersion of responses around the mean, hence a high level of consistency among respondents. The skewness values are predominantly negative, implying that responses are slightly skewed toward the higher end of the scale, which further supports the positive perception of AI's role in auditing.

The descriptive statistics reveal that the respondents strongly perceive AI as an important tool for improving audit efficiency, strengthening decision-making, and reshaping auditors' professional roles, though not without certain implementation challenges.

4.3 Presentation of Demographics

This section presents the demographic characteristics of respondents who participated in the study. The demographic variables considered include gender, age, educational qualification, years of experience, professional qualification, and type of organization. Understanding these characteristics is essential for interpreting the data accurately, as they provide context regarding the diversity and representativeness of the sample used in analyzing the impact of Artificial Intelligence (AI) on audit efficiency in the private sector.

Table 4.2 Gender Distribution of Respondents

Gender	Count	Percentage
Male	67	56%
Female	52	43%
Prefer not to say	1	1%
Total	120	1

Table 4.2 presents the gender distribution of respondents. Out of the total 120 participants, 67 (56%) were male, 52 (43%) were female, while 1 respondent (1%) preferred not to disclose their gender. This indicates a fairly balanced gender representation, suggesting that both male and female perspectives were adequately captured in the study, ensuring that the findings reflect a gender-diverse view of audit and financial performance perceptions.

Table 4.3 Age distribution of Respondents

Age Group	Count	Percentage
18-25	91	76%
26-35	12	10%
36-45	11	9%
46 and above	6	5%
Total	120	1

As indicated in Table 4.3, the data show that a majority of participants, 91 (76%), were aged between 18 and 25 years, followed by 12 (10%) aged between 26 and 35 years, 11 (9%) between 36 and 45 years, and 6 (5%) aged 46 years and above. This distribution indicates that most respondents were relatively young professionals, reflecting the growing participation of younger individuals in audit and corporate governance-related activities within the Nigerian financial environment.

Table 4.4 Educational Distribution of Respondents

Education	Count	Percentage
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B.sc	44	37%
ND/HND	11	9%
M.Sc	2	2%
Others	19	16%
Total	120	1

Table 4.4 shows the educational qualifications of respondents. The findings reveal that 44 (37%) of the respondents held a Bachelor’s degree (B.Sc.), 11 (9%) possessed a National Diploma or Higher National Diploma (ND/HND), 2 (2%) had a Master’s degree (M.Sc.), while 19 (16%) reported other forms of qualifications. This pattern suggests that the majority of respondents were university graduates, providing a well-educated base of participants who are likely to have sufficient understanding of audit processes and financial reporting issues.

Table 4.5 Years of Experience distribution among Respondents

Years of Experience	of audit	Count	Percentage
No experience		27	23%
Less than 2 years		48	40%
2-5 years		20	17%
6-10years		5	4%
Total		120	1

Table 4.5 presents the distribution of respondents by their years of experience. The results indicate that 27 (23%) had no prior audit experience, 48 (40%) had less than two years of experience, 20 (17%) had between two and five years of experience, and 5 (4%) had between six and ten years of experience. This suggests that most of the respondents were at the early stages of their professional careers, which may imply a youthful but emerging workforce with developing expertise in auditing and financial management.

Table 4.6 Profession Qualification distribution among Respondents

Profession Qualification	Count	Percentage
ICAN	25	21%
ACCA	6	5%
CPA	2	2%
Others	21	18%
None	64	53%
Total	120	1

Table 4.6 highlights the professional qualifications of respondents. The results show that 25 (21%) were members of the Institute of Chartered Accountants of Nigeria (ICAN), 6 (5%) were affiliated with the Association of Chartered Certified Accountants (ACCA), 2 (2%) held the Certified Public Accountant (CPA) qualification, and 21 (18%) had other professional certifications. Meanwhile, 64 (53%) of the respondents reported having no professional qualification. This distribution suggests a blend of certified professionals and trainees in the sample, providing a balanced insight from both experienced and aspiring practitioners in the auditing field.

Table 4.7 Type of Organization distribution among Respondents

Type of Organization	Count	Percentage
Audit firm	18	14%
Corporate organization	43	33%
Others	58	53%
Total	120	1

Table 4.7 shows the distribution of respondents based on their organizational affiliation. The data reveal that 18 (14%) were employed in audit firms, 43 (33%) worked in corporate organizations, while 58 (53%) belonged to other types of organizations. This reflects a diverse organizational representation, ensuring that the study captures perspectives from both

audit professionals and corporate employees, thereby enriching the overall analysis of audit quality and financial performance relationships.

4.4 Pearson Correlation Coefficient

	<i>AI</i>	<i>AE</i>	<i>CAC</i>	<i>AIS</i>	<i>AJD</i>
<i>AI</i>	1				
	0.631499				
<i>AE</i>	2	1			
	0.728453				
<i>CAC</i>	8	0.36407	1		
	0.789853	0.58522	0.44927		
<i>AIS</i>	2	8	7	1	
	0.813474	0.54512	0.54457	0.67856	
<i>AJD</i>	2	5	6	1	1

Table 4.8 presents the Pearson correlation coefficients showing the strength and direction of the linear relationships among the key variables in the study, Artificial Intelligence (AI), Audit Efficiency (AE), Challenges in Adopting AI Tools (CAC), Impact of AI on Auditors' Skills and Roles (AIS), and AI Support for Auditors' Judgment and Decision-Making (AJD). Correlation analysis helps to determine the degree of association between the dependent variable (AI) and the independent variables before proceeding to the regression analysis.

The results indicate that all independent variables are positively correlated with AI, implying that as each of these factors increases, the adoption or impact of Artificial Intelligence in auditing also tends to increase. The strongest positive correlation is observed between AI and AJD ($r = 0.813$), suggesting a very strong linear relationship between AI and auditors' professional judgment and decision-making. This finding supports the notion that AI tools significantly enhance auditors' analytical capabilities and decision support functions (Brown-Liburd et al., 2021).

Similarly, AI and AIS ($r = 0.790$) show a strong positive relationship, implying that as AI technologies become more integrated into audit processes, there is a corresponding evolution in the roles, skills, and competencies required of auditors. This agrees with the assertion of Issa, Sun, and Vasarhelyi (2016) that AI is redefining the audit profession by emphasizing analytical and technological skills over traditional manual procedures.

The correlation between AI and CAC ($r = 0.728$) is also strong and positive, indicating that the more challenges organizations face in adopting AI, the more attention and awareness there tends to be around AI implementation within the audit function. This may reflect that increased exposure to AI tools often brings greater recognition of the associated challenges, such as cost, data quality, and technical expertise constraints.

Furthermore, AI and AE ($r = 0.631$) exhibit a moderate to strong positive correlation, showing that the application of AI technologies contributes meaningfully to improved audit efficiency. This finding aligns with prior research (Appelbaum, Kogan & Vasarhelyi, 2017) emphasizing that AI-driven analytics can streamline audit tasks and enhance performance accuracy.

The inter-correlations among the independent variables (AE, CAC, AIS, and AJD) are also positive but moderate, ranging between $r = 0.36$ and $r = 0.68$. These moderate relationships suggest that while the variables are related, they measure distinct dimensions of AI's impact on auditing, thereby reducing the risk of multicollinearity in the regression model.

In summary, the correlation analysis reveals a generally strong and positive relationship among all variables, suggesting that Artificial Intelligence is closely associated with improvements in audit efficiency, changes in auditors' roles and skills, enhanced judgment and decision-making, and recognition of adoption challenges. These findings provide a solid

foundation for the subsequent regression analysis, which examines the extent and significance of these relationships.

4.5.1 Analysis of Regression Results

Table 4.7 Ordinary Least Square Regression

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R	0.9315							
R Square	0.8677							
Adjusted R Square	0.8616							
Standard Error	0.1897							
Observations	120							

ANOVA								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	4	20.52983	5.132458	142.6113	2.4E-37			
Residual	87	3.131055	0.035989					
Total	120	23.66089						

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	0.0350	0.1742	0.2007	0.8414	-0.3113	0.3812	0.3113	0.3812
AE	0.1014	0.0386	2.6260	0.0102	0.0246	0.1781	0.0246	0.1781
CAC	0.2765	0.0366	7.5634	0.0000	0.2038	0.3491	0.2038	0.3491
AIS	0.3178	0.0539	5.9014	0.0000	0.2108	0.4248	0.2108	0.4248
AJD	0.3140	0.0572	5.4921	0.0000	0.2004	0.4276	0.2004	0.4276

The model summary in Table 4.9 shows a Multiple R value of 0.9315, indicating a very strong positive relationship between AI and the combined independent variables. The R Square value of 0.8677 reveals that approximately 86.8% of the variation in Artificial Intelligence adoption or impact can be explained by the four predictors (AE, CAC, AIS, and AJD). The Adjusted R Square (0.8616) further confirms the model's robustness after adjusting for the number of predictors. This high coefficient of determination suggests that the model provides an excellent fit, implying that these variables jointly have a strong influence on AI integration in auditing.

4.5.2 Hypothesis Testing

Hypothesis One:

AI technologies have no significant impact on audit efficiency compared to traditional audit methods.

The regression coefficient for Audit Efficiency (AE) is 0.1014 with a t-value of 2.626 and a p-value of 0.0102, which is less than 0.05. This indicates that AE has a statistically significant and positive effect on AI adoption. The null hypothesis (H_{01}) is rejected, implying that AI technologies significantly improve audit efficiency compared to traditional audit methods. This finding supports prior research (Appelbaum, Kogan & Vasarhelyi, 2017) that AI enhances the speed, accuracy, and coverage of audit procedures.

Hypothesis Two:

Auditors do not face significant challenges in adopting AI-driven tools.

The regression result for Challenges in Adopting AI Tools (CAC) shows a coefficient of 0.2765, a t-value of 7.563, and a p-value of 0.000, which is well below the 0.05 threshold. This means that challenges in AI adoption significantly influence the level of AI

implementation in auditing. The null hypothesis (H_{02}) is rejected, indicating that auditors indeed face significant challenges, such as high implementation costs, lack of technical expertise, and data quality concerns, when adopting AI tools. This is consistent with the findings of Krieger, Drews, and Velte (2021), who emphasized that such barriers hinder full AI integration in audit practice.

Hypothesis Three:

The integration of AI in auditing has no significant effect on the roles and skills required of auditors in the future.

For the variable representing the Impact of AI on Auditors' Skills and Roles (AIS), the coefficient is 0.3178, with a t-value of 5.901 and a p-value of 0.000. Since the p-value is less than 0.05, the effect is statistically significant. The null hypothesis (H_{03}) is rejected, meaning that the integration of AI significantly affects the roles and skill sets required of auditors. This supports the assertion of Issa, Sun, and Vasarhelyi (2016) that auditors are expected to acquire data analytics and technological competencies to remain relevant in an AI-driven audit environment.

Hypothesis Four:

AI does not significantly support auditors' professional judgment and decision-making during audits.

The regression coefficient for AI Support for Auditors' Judgment and Decision-Making (AJD) is 0.3140, with a t-value of 5.492 and a p-value of 0.000. Since the p-value is below 0.05, the relationship is statistically significant. The null hypothesis (H_{04}) is rejected, confirming that AI significantly supports auditors' professional judgment and decision-making. This aligns with Brown-Liburd et al. (2021), who noted that AI assists auditors in interpreting complex data and enhancing the quality of audit judgments, provided human oversight is maintained.

4.6 Discussion of Findings

The results of this study provide substantial evidence that Artificial Intelligence (AI) has a significant and positive impact on audit efficiency within private sector organizations in Benin City, Edo State. The findings are consistent across the descriptive statistics, correlation analysis, and regression outputs, confirming that AI plays a transformative role in modern auditing processes. The discussion below integrates these empirical findings with the study's objectives and existing literature.

The descriptive statistics revealed high mean scores across all variables, indicating that respondents generally perceive AI as a valuable tool that enhances audit performance, improves decision-making, and reshapes auditors' professional roles. The strong mean value for the impact of AI on auditors' skills and roles (Mean = 4.16) particularly underscores the belief that AI is redefining the competencies required in the audit profession. This aligns with Issa, Sun, and Vasarhelyi (2016), who argue that AI adoption necessitates new technical proficiencies such as data analytics, algorithm interpretation, and IT governance, thereby transforming the auditor's traditional role.

The correlation analysis showed strong positive relationships between AI and the four independent variables, Audit Efficiency ($r = 0.63$), Challenges in Adopting AI ($r = 0.73$), Impact on Auditors' Skills and Roles ($r = 0.79$), and AI Support for Judgment and Decision-Making ($r = 0.81$). These results indicate that as AI becomes more integrated into audit functions, there are corresponding increases in audit efficiency, the need for new skill sets, and the enhancement of professional judgment. The high inter-variable correlations also reflect the interconnected nature of AI's influence across different dimensions of audit practice. This observation corroborates the views of Appelbaum, Kogan, and Vasarhelyi (2017), who emphasize that AI's integration in auditing extends beyond automation, it reshapes audit methodologies, professional expectations, and assurance quality.

The regression results further validate these findings by showing that all four predictors significantly influence AI's role in auditing. The high coefficient of determination ($R^2 = 0.8677$) suggests that approximately 87% of the variations in AI adoption and effectiveness can be explained by audit efficiency, challenges in AI adoption, auditors' skill transformation, and AI-supported judgment. This demonstrates that these factors jointly capture the critical dimensions of AI's impact on the auditing landscape.

Specifically, the positive and significant coefficient for Audit Efficiency ($\beta = 0.101$, $p < 0.05$) implies that AI technologies considerably enhance audit quality and reduce time spent on routine procedures. This supports Kokina and Davenport (2017), who assert that AI improves the scope and precision of audits by allowing auditors to test entire data populations rather than limited samples. Similarly, the significant relationship between Challenges in AI Adoption ($\beta = 0.277$, $p < 0.01$) and AI underscores the reality that while AI offers numerous benefits, its implementation is often hindered by barriers such as high costs, data security issues, and inadequate expertise. This finding mirrors the conclusions of Krieger, Drews, and Velte (2021), who identified such challenges as key deterrents to full AI integration within audit firms.

Moreover, the significant influence of AI on auditors' skills and roles ($\beta = 0.318$, $p < 0.01$) indicates that the introduction of AI is redefining professional boundaries and responsibilities. Auditors are now expected to act as interpreters of complex data-driven insights rather than merely as verifiers of transactions. This transformation aligns with Alles, Kogan, and Vasarhelyi (2018), who argue that AI has shifted auditing toward a more analytical and strategic function that contributes to organizational decision-making.

The strong positive effect of AI on auditors' professional judgment and decision-making ($\beta = 0.314$, $p < 0.01$) highlights AI's role as a powerful decision-support mechanism. By

providing analytical insights and detecting anomalies in large data sets, AI tools enhance auditors' ability to exercise professional skepticism and make informed judgments. This is consistent with Brown-Liburd et al. (2021), who posit that AI serves as an augmentative tool that enhances rather than replaces human judgment, thereby improving the reliability and timeliness of audit outcomes.

Collectively, these findings reinforce the notion that Artificial Intelligence represents both an opportunity and a challenge for the auditing profession. On one hand, it enhances efficiency, analytical depth, and decision quality; on the other, it demands new competencies and raises concerns about transparency, accountability, and implementation complexity. Nevertheless, the results of this study indicate that the overall impact of AI on audit practice in the private sector is overwhelmingly positive, confirming its role as a strategic enabler of innovation and audit excellence.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION, AND RECOMMENDATIONS

5.1 Introduction

The integration of Artificial Intelligence (AI) into auditing has become one of the most transformative developments in contemporary accounting and assurance practices. This study examined the impact of AI on audit efficiency in the private sector, focusing on how AI technologies influence audit processes, the challenges associated with their adoption, their effects on auditors' skills and roles, and their support for professional judgment and decision-making.

This chapter presents a comprehensive summary of findings derived from the analysis in Chapter Four, draws conclusions based on empirical results, and provides recommendations for practitioners, policymakers, and educators to enhance the adoption and effective use of AI in auditing.

5.2 Summary of Findings

This research investigated the impact of Artificial Intelligence (AI) on audit efficiency in the private sector. Four explanatory variables were employed—Audit Efficiency (AE), Challenges in Adopting AI Tools (CAC), Impact of AI on Auditors' Skills and Roles (AIS), and AI Support for Auditors' Judgment and Decision-Making (AJD)—while AI served as the dependent variable. Using descriptive statistics, correlation analysis, and multiple regression, the study tested four hypotheses.

The major findings are summarized as follows:

AI significantly improves audit efficiency.

The regression results revealed a positive and statistically significant relationship between AI and audit efficiency ($\beta = 0.101$, $p < 0.05$).

Auditors face notable challenges in adopting AI-driven tools.

The study found that challenges such as high implementation costs, lack of technical expertise, and data privacy concerns significantly affect AI adoption ($\beta = 0.277$, $p < 0.01$).

The integration of AI significantly affects auditors' skills and professional roles.

The coefficient for the impact of AI on auditors' skills and roles ($\beta = 0.318$, $p < 0.01$) was positive and significant.

AI significantly supports auditors' professional judgment and decision-making.

The results also revealed a strong positive relationship between AI and auditors' professional judgment ($\beta = 0.314$, $p < 0.01$).

5.3 Conclusion

This study examined the relationship between Artificial Intelligence and audit efficiency in the private sector, focusing on how AI technologies influence the audit process, the challenges of adoption, and their effects on auditors' professional development and decision-making capacity.

The findings demonstrated that AI significantly enhances audit efficiency by improving accuracy, speed, and analytical depth. However, its successful adoption is often constrained by implementation challenges such as limited technical expertise, high costs, and organizational resistance to technological change. Furthermore, AI integration is redefining

the auditor's role from that of a traditional compliance officer to that of a strategic analyst capable of interpreting data-driven insights.

The study also concluded that AI serves as a valuable decision-support tool, augmenting rather than replacing human judgment. It enhances professional skepticism and objectivity, allowing auditors to identify risks and irregularities more effectively.

Overall, the research establishes that the adoption of AI in auditing offers vast potential for innovation, efficiency, and value creation in the private sector. However, maximizing these benefits requires addressing adoption barriers and equipping auditors with the necessary digital competencies to thrive in an AI-driven audit environment.

5.4 Recommendations

Based on the findings of this study, the following recommendations are made to enhance the effective integration of AI in auditing:

Promote Capacity Building and Digital Training for Auditors:

Professional bodies and firms should organize continuous training programs to equip auditors with AI-related skills such as data analytics, machine learning, and automation tools to remain relevant in the evolving audit landscape.

Encourage Organizational Investment in AI Infrastructure:

Firms should allocate adequate resources toward developing or acquiring reliable AI systems that can streamline audit processes, enhance data quality, and reduce human error.

Address Implementation Barriers:

Management should proactively address barriers such as cost, data privacy, and system compatibility by developing clear AI adoption strategies and collaborating with technology providers.

Integrate AI into Professional Audit Standards and Education:

Regulatory and professional bodies such as ICAN and ACCA should integrate AI competencies into audit standards and certification curricula to ensure future auditors are adequately prepared for technology-driven auditing.

Leverage AI for Decision-Support, Not Replacement:

Firms should use AI as a complementary tool to enhance human judgment, not as a substitute for professional reasoning. AI outputs should always be reviewed critically by qualified auditors to maintain accountability and ethical standards.

Foster Collaboration Between Auditors and IT Experts:

Effective AI deployment requires collaboration between auditors, data scientists, and IT professionals to ensure that AI tools are properly designed, interpreted, and utilized for audit objectives.

Encourage Further Research and Policy Support:

Policymakers should support research into AI adoption frameworks for the accounting profession to create standardized guidelines that balance technological innovation with ethical and professional considerations.

5.5 Suggestions for Further Research

To deepen understanding and expand on the findings of this study, future research could consider the following areas:

Sector-Specific Analysis:

Examine the impact of AI adoption on audit efficiency across different sectors such as banking, manufacturing, and telecommunications to identify sectoral variations.

Longitudinal Studies:

Investigate the long-term effects of AI integration on audit quality and firm performance over multiple years.

Comparative Studies:

Compare the adoption and impact of AI in auditing between public and private sector organizations, or between developing and developed countries.

Exploration of Ethical Implications:

Examine ethical and regulatory challenges surrounding the use of AI in auditing, including data privacy, transparency, and accountability issues.

AI Adoption Readiness Models:

Develop frameworks to assess the readiness of audit firms to adopt AI technologies, taking into account factors such as culture, infrastructure, and employee attitudes.

AI and Auditor Independence:

Explore how AI influences auditor independence, professional skepticism, and the overall credibility of financial reporting.

AI and Fraud Detection:

Future studies can also focus on how AI-based auditing systems enhance fraud detection, risk assessment, and compliance monitoring.

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APPENDIX
DEPARTMENT OF ACCOUNTING
FACULTY OF MANAGEMENT SCIENCES
UNIVERSITY OF BENIN, BENIN CITY, EDO STATE

QUESTIONNAIRE ON ARTIFICIAL INTELLIGENCE AND AUDIT EFFICIENCY

Dear Respondent,

I am Ighodaro Osayabamwen Martha, a final-year student in the Department of Accounting, Faculty of Management Sciences, conducting a research study titled “Artificial Intelligence (AI) and Audit Efficiency.”

This research is being carried out in partial fulfillment of the requirements for the award of a Bachelor of Science (B.Sc.) degree in Accounting.

The purpose of this study is to examine the impact of AI technologies on audit efficiency compared to traditional audit methods, to evaluate the challenges faced by auditors in adopting AI-driven tools, and to ascertain the extent to which AI improves audit quality and effectiveness.

Your participation is highly valuable to the success of this study. Please be assured that all information provided will be treated with the utmost confidentiality and used solely for academic purposes. Kindly respond honestly to all questions, as your input will contribute greatly to the generation of meaningful findings and recommendations.

Thank you for your time and cooperation.

Yours faithfully,

Ighodaro Osayabamwen Martha
(Researcher)

Please tick (✓) the option that best represent your view.

SECTION A: DEMOGRAPHIC INFORMATION

1. Gender	<input type="checkbox"/> Male <input type="checkbox"/> Female <input type="checkbox"/> Prefer not to say
2. Age Group	<input type="checkbox"/> 18–25 <input type="checkbox"/> 26–35 <input type="checkbox"/> 36–45 <input type="checkbox"/> 46 and above
3. Educational Qualification	<input type="checkbox"/> ND/HND <input type="checkbox"/> B.Sc <input type="checkbox"/> M.Sc <input type="checkbox"/> Ph.D <input type="checkbox"/> Others
4. Professional Qualification	<input type="checkbox"/> None <input type="checkbox"/> ICAN <input type="checkbox"/> ACCA <input type="checkbox"/> CPA <input type="checkbox"/> Others
5. Years of Auditing Experience	<input type="checkbox"/> Less than 2 years <input type="checkbox"/> 2–5 years <input type="checkbox"/> 6–10 years <input type="checkbox"/> Above 10 years <input type="checkbox"/> No audit experience
6. Type of Organization	<input type="checkbox"/> Audit firm <input type="checkbox"/> Corporate organization <input type="checkbox"/> Others

SECTION B: IMPACT OF AI TECHNOLOGIES ON AUDIT EFFICIENCY

Scale: 5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree

S/N	Statements	5	4	3	2	1
1	AI tools improve the accuracy of audit procedures compared to traditional methods.					
2	The use of AI reduces time spent on audit activities.					
3	AI enhances auditors' ability to detect fraud and irregularities.					
4	AI facilitates faster data processing and analysis.					
5	AI improves the reliability of audit findings.					
6	AI reduces human error in audit operations.					
7	Traditional audit methods are less efficient than AI-based audits.					

SECTION C: CHALLENGES IN ADOPTING AI-DRIVEN AUDIT TOOLS

Scale: 5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree

S/N	Statements	5	4	3	2	1
1	High cost of acquiring AI software limits its adoption.					
2	Lack of technical expertise among auditors hinders AI adoption.					
3	Resistance to change from traditional methods reduces AI usage.					
4	Poor IT infrastructure in organizations affects AI implementation.					
5	Lack of awareness of AI benefits delays adoption.					
6	Concerns about data privacy and cybersecurity limit AI use.					
7	Inadequate regulatory framework affects AI application in auditing.					

SECTION D: IMPACT OF AI ON THE FUTURE ROLE AND SKILLS OF AUDITORS

Scale: 5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree

S/N	Statements	5	4	3	2	1
1	AI will shift auditors' focus from manual tasks to analytical work.					
2	Future auditors will need strong IT and data analytics skills.					
3	AI will reduce the need for manual audit testing.					
4	Auditors will need continuous professional training to remain relevant.					
5	AI will enhance auditors' decision-making ability.					
6	AI will create new career opportunities in the audit profession.					
7	Ethical considerations will be more important in AI-driven auditing.					

SECTION E: HOW AI SUPPORTS AUDITORS' JUDGMENT AND DECISION-MAKING

Scale: 5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree

S/N	Statements	5	4	3	2	1
1	AI provides auditors with real-time insights that improve judgment during audits.					
2	AI tools assist auditors in making data-driven decisions.					
3	AI enhances auditors' ability to assess risk and uncertainty objectively.					
4	AI supports consistent decision-making across audit engagements.					
5	AI improves the quality of evidence available for audit judgments.					
6	AI helps auditors identify patterns that influence professional decisions.					
7	AI reduces bias in auditors' decision-					

	making process.					
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Thank you for your participation. Your responses are highly appreciated.