Artificial Intelligence Applications and Financial Reporting Quality among Deposit Money Banks in Nigeria

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BEING A THESIS PRESENTED TO THE DEPARTMENT OF ACCOUNTING, FACULTY OF MANAGEMENT SCIENCE, UNIVERSITY OF BENIN, IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF SCIENCE (M.SC) DEGREE IN ACCOUNTING.

MAY 2026

DECLARATION

I, Angela ASEMOTA do hereby declare that:

i. This thesis is based on a study undertaken by me in the department of Accounting, Faculty of Management Sciences, University of Benin, Benin City, Edo State, under the supervision of Dr. Uyi Obazee.

ii. This thesis has not been previously submitted elsewhere for the award of a Master of Science (M.Sc) degree elsewhere.

iii. All ideas and views are products of my personal research and that of the others duly expressed, appreciated and acknowledged.

iv. Any litigation or liability arising from the thesis is to be borne by me wholly and not that of the supervisor.

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Researcher

Date: ______________________

CERTIFICATION

We certify that this thesis was carried out by **Angela ASEMOTA** in the Department of Accounting, Faculty of Management Sciences, University of Benin, Benin City and it is considered adequate in scope and quality in partial fulfilment of the requirements for the award of M.Sc. Accounting Degree.

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ATTESTATION OF CORRECTED THESIS

We attest that Angela Asemota has successfully carried out all the required corrections as suggested by the External and internal Examiners in her thesis titled Artificial Intelligence Applications and Financial Reporting Quality among Deposit Money Banks in Nigeria.

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Head of Department

DEDICATION

I dedicate this thesis to God Almighty for His grace, mercies and supplies for the pursuit and the successful completion of this Program.

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ABSTRACT

This study investigated artificial intelligence applications in relation to financial reporting quality among deposit money banks in Nigeria. The specific objectives were to examine the extent to which artificial intelligence accounting, artificial intelligence data analytic, artificial intelligence auditing and artificial intelligence predictive applications have influence on financial reporting quality of deposit money banks in Nigeria. This study was a field survey for the year 2025. A total of 2,839 accountants, auditors and management staff constituted the population size, while 351 staff of deposit money banks in Benin City of Edo state formed the sample size by employing stratified and purposive sampling selection techniques. It was a quantitative research design and the main instrument used in collecting data was questionnaire administration. The statistical techniques employed include descriptive statistics, Pearson correlations, variance inflation factor and least squares regression method. The study found that artificial intelligence accounting, data analytic and predictive applications have significant positive t-statistics value of 2.480, 2.441 and 2.796 with a probability value of 0.010 (1%), 0.010 (1%) and 0.005 (0.5%) respectively. It was also revealed that artificial intelligence auditing applications has no significant influence on financial reporting quality among deposit money banks in Nigeria but has positive t-statistics value of 1.634 with a probability value of 0.103 (10%). Thus, the study concluded that artificial intelligence applications in accounting, data analytics, auditing and predictive analytics are critical in facilitating enhancement in financial reporting quality among deposit money banks. It therefore recommended that organisations should take advantages of artificial intelligence innovation by training and developing their accountants, auditors and senior managers in areas of financial transactions analyses and prediction to enhance financial reporting quality for the interest of stakeholders.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Artificial intelligence is increasingly being adopted in financial reporting to enhance the accuracy, efficiency, and reliability of financial information, which is crucial for decision-making by stakeholders such as investors, regulators, and management. Artificial intelligence can be traced back to the mid-20th century when Alan Turing proposed the idea of machines simulating human intelligence through computational methods in 1950 (Mustafa & Elamin, 2024); since then, it has evolved through several stages, from rule-based expert systems to modern neural networks and generative artificial intelligence models. Artificial intelligence is broadly defined as the capability of machines to exhibit intelligent behaviour, including understanding natural language, recognising patterns, and making autonomous decisions (Russell & Norvig, 2021). Artificial intelligence (AI) is a revolutionary area of computer science which allows robots to simulate human cognitive processes, including learning, reasoning, and problem-solving. Advanced technologies such as machine learning, natural language processing and predictive data analytics have significantly enhanced the way financial reports are prepared, analysed and presented (Smith & Johnson, 2022). Artificial intelligence has the potential to address different challenges by automating processes, improving error detection, and providing predictive insights (Warren et al., 2021).

Financial Reporting Quality (FRQ) refers to the extent to which financial statements faithfully represent a company's economic reality, thereby enabling users to make informed decisions. High-quality financial reporting ensures transparency, accountability, and efficiency in financial markets (Aiman et al., 2024).

The International Accounting Standards Board (IASB) highlights two fundamental qualitative characteristics of financial reporting (relevance and faithful representation) as the cornerstone of high-quality reporting. Additionally, enhancing qualitative characteristics such as comparability, verifiability, timeliness, and understandability strengthens the usefulness of financial reports (IASB, 2018). According to the International Accounting Standards Board (2008) and Okoroigwe et al. (2021), the two primary indicators of the quality of corporate information regarding accounting standards are reliability and relevance, which make the information pertinent for decision-makers as well as enhance qualitative attributes such as timeliness, comparability and understandability.

Firms with strong financial reporting quality enjoy lower costs of capital, improved market liquidity, and better corporate governance (Chen, 2025). Conversely, poor-quality reporting, often linked with earnings management or fraudulent practices, undermines trust and can lead to financial scandals, as seen in cases like Enron and WorldCom (Olubusayo & Isiaka, 2024). Moreover, financial reporting quality is closely associated with corporate governance mechanisms. Strong internal controls, effective audit committees, and independent external auditors contribute significantly to ensuring the reliability of financial reports (Shahanif, 2020). Similarly, the adoption of technology, such as artificial intelligence and data analytics, has been recognised as a driver for improved accuracy and transparency in financial reporting (Moll & Yigitbasioglu, 2019). Financial reporting quality plays a vital role in sustaining capital markets, supporting decision-making and fostering trust between corporations and stakeholders. Its effectiveness depends on compliance with international standards, ethical corporate governance, and continuous adaptation to technological and regulatory changes.

In Nigeria, the banking sector has witnessed significant digital transformation driven by advances in information and communication technologies, regulatory reforms, and increasing customer demand for innovative financial services. Deposit money banks have progressively adopted digital platforms, automated transaction processing systems, data analytics tools, and artificial intelligence-enabled applications to improve operational efficiency and service delivery. Studies, such as those by Olayinka and Olaoye (2021), Ononokpono et al. (2023), Oduwole and Fatogun (2023), and Unuesiri and Adejuwon (2024), indicate that artificial intelligence is increasingly influencing banking operations, accounting practices, risk management processes, fraud detection, compliance monitoring, and financial data analysis within the Nigerian banking industry. The Central Bank of Nigeria (CBN) has also encouraged technological innovation through regulatory initiatives aimed at strengthening financial system stability, enhancing risk management practices, and improving transparency in financial reporting (CBN, 2024). Consequently, the growing adoption of artificial intelligence in Nigerian banks has the potential to reduce reporting errors, strengthen internal controls, and enhance financial reporting quality (Ononokpono et al., 2023).

Artificial intelligence technologies such as machine learning (ML), expert systems (ES), natural language processing (NLP), and robotic process automation (RPA) are transforming financial reporting practices. For example, machine learning algorithms can analyse historical financial data to identify patterns and anomalies, supporting auditors in fraud detection and risk assessment. Similarly, Natural Language Processing (NLP) tools are used to process and interpret unstructured data, such as narrative sections of financial statements, enhancing the extraction of valuable insights (Richins et al., 2017). Robotic process automation streamlines repetitive tasks such as journal entries and reconciliations, allowing accountants to focus on strategic activities. Artificial intelligence also supports the demand for real-time financial reporting and predictive analytics. These systems help ensure compliance with regulations by constantly checking for updates in accounting rules and automatically making changes to reporting methods.

Artificial intelligence applications span across different areas such as artificial intelligence accounting applications, AI-data analytics applications, artificial intelligence auditing applications and artificial intelligence predictive applications, which collectively improve the quality and relevance of financial information.

AI-driven accounting automates traditional manual bookkeeping and reporting processes, reducing human errors and increasing operational efficiency. Tools such as Xero, QuickBooks, and Sage now incorporate AI features to categorise transactions, reconcile accounts, and generate financial statements in real time (Issa et al., 2016). By automating repetitive tasks, AI ensures compliance with accounting standards and enhances the timeliness of reporting, which is vital for stakeholders' decision-making (Pan & Seow, 2016). Moreover, AI-based accounting systems can adapt to regulatory changes, reducing the risk of misreporting.

Furthermore, AI-powered analytics in financial reporting enables firms to generate deeper insights from large volumes of financial and non-financial data. Machine learning algorithms and natural language processing (NLP) techniques allow for predictive and prescriptive analytics, which go beyond historical reporting to forecast future performance. For instance, AI analytic tools can detect anomalies in financial transactions, flagging potential fraud or errors before financial statements are finalised (Kokina & Davenport, 2017). In addition, AI-generated narrative reports, often referred to as "robo-writing", simplify complex financial data for investors and regulators, thereby enhancing understandability and transparency.

Furthermore, the integration of artificial intelligence (AI) into auditing has transformed the traditional approach to financial assurance by enhancing efficiency, accuracy, and reliability in detecting anomalies and ensuring compliance. An AI auditing application refers to the use of advanced algorithms, machine learning models, and data analytics tools to perform audit tasks that were previously manual, repetitive, and prone to human error (Kokina & Davenport, 2017). Unlike conventional auditing methods, AI systems can process vast volumes of financial and non-financial data in real time, providing deeper insights into organisational activities and enabling auditors to identify irregularities or fraudulent activities more effectively (Issa et al., 2016). This shift is particularly significant in today's complex financial environment, where organisations generate massive data sets that demand advanced technological support for accurate evaluation.

However, AI auditing applications extend beyond efficiency to include predictive and prescriptive insights, offering auditors the ability to forecast potential risks and recommend preventive measures (Vasarhelyi et al., 2015). Such applications improve audit quality and reinforce stakeholders' trust in financial reporting by minimising biases and enhancing transparency. As regulatory bodies increasingly emphasise audit quality and accountability, the adoption of AI-driven auditing tools positions organisations and auditors to meet the dynamic challenges of modern financial ecosystems (Marwa et al., 2024).

Consequently, artificial intelligence (AI) has increasingly become a transformative tool in financial and business decision-making, particularly through its predictive application. 'Predictive application' refers to the ability of AI systems to analyse historical and real-time data, identify hidden patterns, and forecast future outcomes with a high degree of accuracy (Mikalef et al., 2018). In financial contexts, this artificial intelligence application is especially relevant for forecasting earnings, detecting fraudulent activities, and predicting market fluctuations that influence reporting quality and investor confidence (Okafor et al., 2024). Also, AI's ability to unite with other technologies, such as blockchain, has amplified its impact by ensuring data security, traceability, and compliance with regulatory standards (Ibrahim et al., 2025). The predictive power of AI is not only reshaping how firms interpret data but also enhancing the timeliness and reliability of financial reporting. By leveraging advanced algorithms, auditors and financial managers can anticipate irregularities before they escalate, thus improving the overall quality of decision-making and corporate accountability (Li et al., 2020).

Given the increasing adoption of artificial intelligence technologies within the Nigerian banking industry and the growing emphasis on high-quality financial reporting, it becomes imperative to examine the extent to which artificial intelligence applications in accounting, data analytics, auditing, and predictive analytics influence financial reporting quality among deposit money banks in Nigeria.

1.2 Statement of the Research Problem

The motivation for this study emerged from several contemporary developments in the banking industry; for example, the global financial sector is undergoing rapid digital transformation driven by artificial intelligence technologies such as machine learning, robotic process automation, predictive analytics, natural language processing, and intelligent auditing systems. These technologies have transformed the traditional accounting and reporting processes by enhancing the efficiency and accuracy of financial information and decision-making by stakeholders. Furthermore, issues relating to delayed reporting, information asymmetry, and occasional corporate governance failures have raised questions about the reliability of financial information provided for stakeholders. Furthermore, given the increasing investment in AI technologies by Nigerian banks and the strategic emphasis placed on digital banking by regulators such as the Central Bank of Nigeria, there is a need to provide empirical evidence on whether AI contributes positively to the production of high-quality financial reports.

The integration of artificial intelligence (AI) and financial reporting quality has gained significant attention in recent years (Kumar & Singh, 2019), and it has uniquely transformed how organisations process, analyse, and report financial data. Artificial intelligence offers promising benefits, which include improved accuracy, efficiency, and fraud detection. Recent studies like Zhang et al. (2021) and Ononokpono et al. (2023) highlight that artificial intelligence technologies are increasingly becoming indispensable in the banking sector. These technologies facilitate the automation of complex tasks in accounting, data analytics, auditing, and predictive applications in areas such as fraud detection, credit scoring, and personalised financial services, thus enabling banks to maintain a competitive edge in a rapidly digitalising world (Unuesiri & Adejuwon, 2024). As banks continue to integrate artificial intelligence into their operations, particularly financial reporting, it is crucial to understand the implications of these technologies on the quality of their financial reports.

There are limited studies from Nigeria and other developing countries that examined artificial intelligence applications on financial reporting quality from other perspectives. Wilson-Oshilim and Efedhoma (2024) explored the impact of artificial intelligence (AI) on financial reporting accuracy and efficiency among Nigerian companies across various sectors. Abubakr et al. (2024) examined the Impact of AI Applications on Corporate Financial Reporting Quality: Evidence from UAE Corporations. Shah (2025) explored the influence of artificial intelligence (AI) adoption on the timeliness of financial reporting among publicly listed firms. Arefeh (2024) examined the impact of accounting software on enhancing the accuracy and timeliness of financial reports. Oleimat et al. (2025) examined the impact of artificial intelligence on the quality of financial reports. Mohammed & Madloul (2025) examined the reflection of artificial intelligence technology on improving the quality of financial reports in commercial banks. Ogungbangbe and Alexanda (2024) investigated artificial intelligence and financial sector regulation: implications for accountants in the Nigerian economy.

Additionally, Oduwole and Fatogun (2023) critically examined the impact of artificial intelligence on accounting practice in the Nigerian banking industry. Furthermore, Ndidiamaka and Chinedu (2025) investigated the effect of artificial intelligence on predictive financial analysis in selected deposit money banks in Anambra State, Nigeria. The gap in knowledge, therefore, presents an opportunity to explore the impact of artificial intelligence applications in accounting, data analytics, auditing, and predictive analytics on the quality of financial reporting among deposit money banks in Nigeria.

1.3 Research Questions

Against the above-identified research problem, the central question is, 'What is the impact of artificial intelligence applications on financial reporting quality among deposit money banks in Nigeria?' The specific questions raised for the study are:

1. To what extent does an artificial intelligence accounting application influence financial reporting quality in Nigerian banks?

2. What is the effect of artificial intelligence data analytics applications on financial reporting quality in Nigerian banks?

3. To what extent does the artificial intelligence auditing application influence financial reporting quality in Nigerian banks?

4. What is the effect of artificial intelligence predictive applications on financial reporting quality in Nigerian banks?

1.4. Objectives of the Study

The broad objective of this study is to explore the impact of Artificial Intelligence (AI) applications on Financial Reporting Quality (FRQ) among deposit money banks.

Specifically, the study's objectives are to:

1. determine the extent to which artificial intelligence accounting applications have influence on financial reporting quality among banks in Nigeria;

2. examine the effect of artificial intelligence data analytics applications on financial reporting quality among banks in Nigeria;

3. ascertain the extent to which Artificial Intelligence auditing application have influence on financial reporting quality among banks in Nigeria; and

4. examine the effect of artificial intelligence predictive applications on financial reporting quality among banks in Nigeria.

1.5. Research Hypotheses

Based on the research questions and objectives of this study, the study specified the hypotheses in null form as follows:

H_{01}: Artificial intelligence accounting application has no significant influence on financial reporting quality among banks in Nigeria.

H_{02}: Artificial intelligence data analytics application has no significant effect on financial reporting quality among banks in Nigeria.

H_{03}: Artificial intelligence auditing application has no significant influence on financial reporting quality among banks in Nigeria.

H_{04}: Artificial intelligence predictive application has no significant effect on financial reporting quality among banks in Nigeria.

1.6. Scope of the Study

Artificial intelligence is proxied with AI accounting, data analytics auditing, and predictive applications in relation to financial reporting quality in Nigeria. Due to the geographical spread of artificial intelligence usage related to financial reporting quality among corporate organisations in Nigeria, this study focuses specifically on deposit money banks located in

Benin City, which is part of the Edo South Central Senatorial District in the South-South geopolitical zone. The choice of Benin City is that all the banks in operation in Edo State have their regional headquarters and offices in Benin City, which makes it imperative for the study. It is a cross-sectional survey for the year 2025. The rationale for the choice of deposit money banks is due to frequent irregularities in financial reports among banks, especially in the past, that led to the sack of CEOs and directors. For instance, Oceanic Bank, Intercontinental Bank, and Afribank faced challenges from financial mismanagement, culminating in the revocation of their banking licences in 2011. More recent incidents highlight that such fraudulent activities remain prevalent. In 2023, First City Monument Bank (FCMB) reported nearly ₦1 billion in fraud-related losses (Financial Institution Training Centre, 2024), while Guarantee Trust Bank was implicated in profit manipulation and the unauthorised opening of accounts (Olumuyiwa, 2024). The most recent case is the 2024 collapse of Heritage Bank that underscored the severity of continued misreporting.

1.7 Significance of the Study

The findings of this study will be beneficial to deposit money banks in Nigeria by providing empirical evidence on how artificial intelligence applications can enhance financial reporting quality. Specifically, the study will demonstrate how the adoption of artificial intelligence in accounting, data analytics, auditing, and predictive analysis can improve the accuracy, reliability, timeliness, and transparency of financial reports. The findings will also assist banks in reducing reporting errors, strengthening internal control systems, and improving compliance with regulatory requirements.

The study will be valuable to accountants, auditors, and other financial reporting professionals within the banking sector. The findings will reveal how artificial intelligence technologies can support routine accounting functions, improve audit procedures, facilitate fraud detection, and enhance the quality of financial information available for decision-making. This may encourage greater integration of artificial intelligence tools into professional accounting and auditing practices.

The study will also benefit the management of deposit money banks by providing evidence of the strategic value of artificial intelligence applications in financial reporting processes. The findings may assist managers in making informed decisions regarding investments in artificial intelligence technology, staff training, and digital transformation initiatives aimed at improving organisational efficiency and reporting quality.

Furthermore, the study will be useful to shareholders, investors, and other users of financial statements. Improved financial reporting quality resulting from the effective application of artificial intelligence can enhance confidence in reported financial information and support more informed investment and economic decisions. The findings will equally be beneficial to regulatory and professional bodies such as the Central Bank of Nigeria (CBN), Financial Reporting Council of Nigeria (FRCN), Chartered Institute of Bankers of Nigeria (CIBN), and the Institute of Chartered Accountants of Nigeria (ICAN). The study will provide evidence that may assist in the formulation of policies, guidelines, and professional standards relating to the adoption and governance of artificial intelligence in financial reporting and related activities within the banking industry.

Finally, the study will contribute to the existing body of knowledge on artificial intelligence and financial reporting quality. It will serve as a useful reference material for researchers, scholars, and students interested in artificial intelligence applications, accounting information systems, financial reporting, and banking sector studies. The findings may also stimulate further empirical research in this emerging area of study.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This section discussed relevant concept and variables that were used in the study. The variables include artificial intelligence Artificial Intelligence accounting application, Artificial Intelligence data analytic application, Artificial Intelligence Auditing application and Artificial Intelligence Predictive application. The concepts discussed were financial reporting, financial reporting quality, current issues in financial reporting, key metrics and indicators of financial reporting quality, Artificial intelligence, artificial intelligence technologies such as machine learning, expert system and natural language processing. Also discussed were artificial intelligence applications in financial reporting; each of the variables (AI application in accounting, data analytics, auditing and prediction) were discussed in relation to financial reporting quality and also in relation to Nigeria banks This chapter further presented various review of related empirical studies, theories which underpinned the study and was concluded with a gap in literature.

2.1 Conceptual Review

2.1.1 Financial Reporting

Financial reporting is the process of giving external parties like creditors, investors, regulators etc.; financial information about a business. The goal is to communicate a company's financial performance and position, thereby enabling stakeholders to make informed decisions (Agustina, 2024). Financial statements, such as the income statement, cash flow statement, statement of financial position and statement of changes in equity, make up financial reports. The main objective of financial reporting is to provide relevant and reliable financial information that is useful for decision-making (FASB, 2010). According to the Financial Accounting Standards Board (FASB), financial reports should provide information about an entity’s statement of financial position and financial performance

(FASB, 2010). These reports assist users in evaluating the solvency, liquidity, and profitability of the business.

Financial reporting is governed by various accounting standards and regulations that ensure consistency and comparability of financial information. The two frameworks that are widely accepted are Generally Accepted Accounting Principles (GAAP) and International Financial Reporting Standards (IFRS). IFRS is used globally, while GAAP is predominantly used in the United States (Wali & Velasco, 2024). These frameworks guarantee that financial statements present an accurate and impartial picture of the company's financial health and offer criteria for reporting financial activities. The Statement of Financial Position, Income Statement, Statement of Cash Flows, and Statement of Change in Equity are the essential parts of financial statements.

A Statement of financial position is a snapshot of a company's financial position at a particular point in time, showing assets, liabilities, and equity while the Income Statement reports the company's performance over a period, highlighting revenues, expenses, and net income (Osadchy et al., 2018). Furthermore, Statement of Cash Flows is a statement detailing the cash inflows and outflows during a period and is divided into operating, investing, and financing activities (Schroeder et al., 2019). Finally Statement of Changes in Equity is a statement that shows changes in the equity section of the statement of financial position, reflecting items such as retained earnings, stock issuance, or dividend payments (Kieso et al., 2016).

2.1.2 Financial Reporting Qualities

Financial reporting is essential for providing transparency and accountability in an organization's financial performance. Financial reporting serves as a critical medium through which organizations communicate their financial performance, position, and prospects to stakeholders, like investors, creditors, regulators, and the public. The quality of financial reporting is essential because it directly influences decision-making, capital allocation, and market efficiency (Zhang & Zhao, 2023). High-quality financial reporting reduces information asymmetry, enhances investor confidence, and mitigates the risks of misrepresentation and fraud (Khan & Safdar, 2024).

According to the International Accounting Standards Board (IASB), the conceptual framework emphasizes that financial information should possess certain qualitative characteristics to be useful to users. These qualities are broadly classified into fundamental characteristics such as relevance and faithful representation and enhancing characteristics such as comparability, verifiability, timeliness, and understandability (IASB, 2018). The presence of these attributes ensures that financial reports provide a true and fair view of an entity's financial performance and position.

The assessment of financial reporting quality has become increasingly important in the context of globalization, corporate scandals, and the need for transparent governance and as such, exploring the fundamental and enhancing qualitative characteristics offers valuable insights into how financial reports achieve credibility and usefulness for decision-making purposes (Olubusayo & Isiaka, 2024).

Fundamental Qualitative Characteristics are Relevance and Faithful Representation.

Relevance is the capacity in which financial information influences the economic decisions of users by helping them evaluate past, present, or future events or confirm prior expectations (IASB, 2018). Information is considered relevant when it has predictive value, confirmatory value, or both. For instance, earnings forecasts or cash flow projections are relevant because they assist investors and creditors in assessing future performance (Azar et al., 2019).

Faithful representation means that financial information accurately reflects the underlying economic phenomena. For information to be faithfully represented, it must be complete, neutral, and free from error (IASB, 2018). Completeness ensures all necessary information is provided; neutrality eliminates bias in preparation and freedom from error enhances accuracy. Without faithful representation, financial information loses credibility, even if it is relevant (Neel & Safdar, 2023).

The Enhancing qualitative characteristics of financial reports are Comparability, Verifiability, Timeliness and Understandability.

Comparability enables users to identify similarities and differences between financial reports across time and among different entities. Consistency in applying accounting policies enhances comparability, making it easier for stakeholders to analyze trends and performance (Martens et al., 2020).

Verifiability implies that different knowledgeable and independent observers could reach consensus that financial information faithfully represents the economic reality it purports to depict (IASB, 2018). Verification may be direct, such as through physical count of assets, or indirect, such as recalculating outputs using the same assumptions.

Timeliness requires that information be available to decision-makers before it loses relevance. Delayed reporting reduces the usefulness of financial information in influencing economic decisions (Kythreotis & Constantinou, 2016). For example, outdated earnings data may be less valuable for investors making immediate capital allocation decisions.

Understandability means financial information should be presented clearly and concisely, enabling users with reasonable financial knowledge to comprehend it. Complex transactions should be explained in a manner that avoids obscurity without oversimplifying essential details (IASB, 2018).

2.1.3 Current Issues in Financial Reporting

Advancements in technology, such as cloud computing and artificial intelligence, have transformed financial reporting. Automation tools can now produce reports more quickly and accurately, which reduces human error and improves efficiency (Deloitte, 2021). There has also been a growing focus on non-financial reporting, specifically Environmental, Social, and Governance (ESG) factors. These factors offer a wider view of a company's performance and risks (Eccles & Klimenko, 2019).

Financial reporting is constantly changing to keep up with shifts in the global economy, new technology, and changing regulatory demands. Several key trends have emerged recently that highlight the increasing complexity of financial reporting and its expanded role in corporate transparency. These trends include a greater focus on non-financial disclosures, the influence of technology, the rise of integrated reporting, and updates to accounting standards. One notable trend in financial reporting is the heightened focus on non-financial disclosures, especially in areas concerning environmental, social, and governance (ESG) issues. Investors, regulators, and other stakeholders are increasingly looking for information on how companies tackle sustainability, climate change, social responsibility, and governance practices (Eccles & Klimenko, 2019).

Consequently, companies are often encouraged or required to share their ESG performance alongside traditional financial data. This trend is driving the creation of standardized frameworks for ESG reporting, including the Global Reporting Initiative (GRI) and the Sustainability Accounting Standards Board (SASB) standards. Many countries, such as those in the EU are advocating for mandatory ESG reporting as part of broader sustainability regulations (Grewal et al., 2021). The adoption of integrated reporting is also a current concern in financial reporting. Integrated reporting (IR) has gained popularity as companies strive to present a complete view of their performance by merging financial, environmental, social, and governance factors into a single report. The International Integrated Reporting Council (IIRC) defines integrated reporting as the process that generates periodic reports explaining how an organization's strategy, governance, performance, and prospects create value over time. This approach aims to overcome the limitations of traditional financial reporting by offering a wider perspective on how companies create value and manage risks (IIRC, 2021). This trend encourages organizations to adopt a more sustainable and long-term perspective on value creation, especially in sectors impacted by environmental and social issues. Advancements in technology and automation are also currently changing financial reporting.

Businesses increasingly use robotic process automation (RPA), machine learning, and artificial intelligence (AI) to improve accuracy, lower human error, and speed up the financial reporting process. Automation tools assist with tasks like data entry, reconciliation, and report generation, enabling companies to produce financial statements more quickly and efficiently (Deloitte, 2021). Additionally, technologies like blockchain are being explored for their potential to improve transparency, security, and traceability in financial transactions, which could change how financial data is recorded and verified. Another emerging trend is the shift toward real-time financial reporting. Traditional financial reporting typically happens quarterly or annually. However, the growing demand for timely information has led some companies to explore real-time reporting or much shorter timelines. This trend is spurred by advances in data analytics and cloud computing, allowing faster processing of financial data and more frequent reporting (KPMG, 2020). Real-time reporting offers investors and stakeholders more immediate insights into a company's performance, helping them make faster decisions in changing market conditions. The convergence of International Financial Reporting Standards (IFRS) and Generally Accepted Accounting Principles (GAAP) is another ongoing trend. While complete convergence hasn't been achieved, efforts are underway to align the two sets of standards to improve comparability and reduce complexity for multinational companies. The International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) are working to harmonize key areas, including revenue recognition, leases, and financial instruments, to provide more consistent and transparent financial reporting across borders (Shruthi, 2016). This trend is especially important as globalization increases the need for uniform accounting practices. The digitalization of financial reporting is also changing how companies manage and report financial data. Cloud-based financial reporting platforms are gaining traction, offering greater flexibility, scalability, and collaboration across departments and locations. These platforms enable real-time access to financial data, automate tasks, and provide robust analytics tools that help companies gain better insights into their financial performance (Deloitte, 2021). Cloud technologies are also lessening the need for manual data entry, which often leads to errors and inefficiencies. Data privacy and cybersecurity concerns have also become significant issues in financial reporting. As financial reporting increasingly depends on digital platforms and technologies, worries about data privacy and cybersecurity have intensified. Cyberattacks, data breaches, and hacking incidents can jeopardize the integrity of financial data and disrupt reporting processes. Companies face growing pressure to implement strong cybersecurity measures to protect sensitive financial information and comply with data protection regulations like the General Data Protection Regulation (GDPR) in Europe (Deloitte, 2021).

As financial data becomes more digitized, protecting this data is vital for maintaining trust and preventing financial fraud. Regulatory changes and global standardization are also trending issues. Besides the push for ESG and non-financial disclosures, regulators worldwide are instituting stricter rules to enhance transparency and corporate governance in financial reporting. The European Union’s Corporate Sustainability Reporting Directive (CSRD) and the U.S. Securities and Exchange Commission’s (SEC) proposals on climate-related disclosures are recent examples of regulatory changes aimed at improving the quality and scope of financial reporting (Grewal et al., 2021). These regulations are helping to standardize reporting requirements across industries and regions, which may ultimately lead to more consistent and comparable financial information globally.

2.1.4 Key Metrics and Indicators in Financial Reporting Quality

Financial reporting quality (FRQ) is essential for ensuring that users of financial statements can make well-informed economic decisions. The International Accounting Standards Board (IASB), through its Conceptual Framework for Financial Reporting, sets out the qualitative characteristics of useful financial information, which serve as key metrics and indicators of FRQ. These characteristics are divided into fundamental qualities (relevance and faithful representation) and enhancing qualities (comparability, verifiability, timeliness, and understandability) (IASB, 2018).

The Fundamental Qualitative Characteristics are Relevance and Faithful representation.

Relevance refers to the capacity of financial information to influence users' economic decisions by helping them evaluate past, present, or future events (IASB, 2018). Metrics of relevance include predictive value (ability to forecast future performance) and confirmatory value (ability to validate prior expectations). High-quality reports present information that is material and avoids unnecessary clutter, thereby enabling users to assess firms' future cash flows (Barth, 2018). Also**,** Faithful representation makes us understand that information accurately depicts the underlying economic phenomena. The three indicators of faithful representation are completeness, neutrality, and freedom from error (IASB, 2018). Completeness ensures that all relevant aspects are disclosed, neutrality implies unbiased presentation, while freedom from error enhances credibility. For instance, the use of fair value measurement under IFRS enhances the faithful representation of financial positions (Kika & Al fatlawi, 2019).

The Enhancing Qualitative Characteristics are Comparability, Verifiability, Timeliness and Understandability. Comparability enables users to identify similarities and differences across entities and reporting periods. Metrics of comparability include consistency of accounting policies and adherence to International Financial Reporting Standards (IFRS), which reduce distortions in cross-border financial analysis (De George et al., 2016).

Verifiability depicts that independent observers can reach consensus that information is faithfully represented. This is indicated by the presence of external audits, reliance on objective evidence, and transparent accounting estimates (Gjoni-Karameta et al., 2021).

Furthermore**,** Timeliness reflects the prompt availability of financial reports before they lose relevance. Indicators include shorter reporting lags, timely disclosures, and adherence to regulatory filing deadlines (Ohaka & Akani, 2017).

Lastly**,** Understandability ensures that financial information is presented clearly and concisely, making it accessible to users with reasonable financial knowledge. Metrics include simplified disclosures, logical classification, and use of plain language in explanatory notes (IASB, 2018).

2.1.5 Artificial Intelligence

The term artificial intelligence (AI) describes how technology especially computer systems, simulate human intelligence processes. These processes include learning, reasoning, problem-solving, perception, and language understanding (Russell & Norvig, 2020). The integration of AI into various domains has revolutionized industries, ranging from accounting, finance, healthcare transportation etc.

The root of Artificial intelligence (AI) can be traced back to classical philosophy, where early thinkers like Aristotle pondered on the nature of reasoning. Artificial Intelligence began in the mid-20th century, with the work of pioneers like Alan Turing, who proposed the famous "Turing Test" as a measure of machine intelligence. In 1956, John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon organized the Dartmouth Conference, marking the formal birth of AI as a scientific discipline (McCarthy et al., 1956).

Artificial Intelligence progressed through several phases and they are the Early Years (1950s–1970s); where early Artificial Intelligence (AI) research focused on symbolic AI and rule-based systems, such as the General Problem Solver (GPS), which tackled mathematical problems through logical reasoning; the next was the AI Winter (1970s–1990s) where due to high expectations and limited progress, AI research faced a downturn, known as the "AI winter," and this led to decrease in funding and interest; this was followed by the resurgence with Machine Learning (1990s–2000s) where the development of more powerful computers and the advent of machine learning (ML) techniques such as decision trees and neural networks, led to the revival in AI research and the last phase was deep Learning and Big Data (2010s–Present) where with the availability of vast amounts of data and advances in hardware, deep learning enabled AI to achieve remarkable successes in fields like image recognition and natural language processing (LeCun et al., 2015).

One of the primary applications of Artificial Intelligence is machine learning, where algorithms analyze data to identify patterns and make decisions with minimal human intervention (Goodfellow et al., 2016). For example, AI systems are widely employed in personalized marketing, predicting consumer behavior, and enhancing customer engagement (Chui et al., 2018). Artificial Intelligence has also found significant applications in healthcare, such as diagnosing diseases, drug development, and predictive analytics. Technologies like neural networks and natural language processing enable early disease detection by analyzing medical data (Esteva et al., 2017). Furthermore, in the area of transportation, autonomous vehicles exemplify Artificial Intelligence's potential like employing sensors and algorithms to navigate and make decisions (Litman, 2021). However, the rise of Artificial intelligence has sparked debates over ethical concerns and potential risks. Issues such as data privacy, bias in algorithms, and job displacement require careful consideration to ensure AI's responsible use (Binns, 2018). Consequently, policymakers and technologists emphasize the need for regulatory frameworks to balance innovation with ethical standards (Floridi & Cowls, 2019).

Artificial intelligence is transforming industries like banking, healthcare, education, and transportation e t c. Furthermore artificial intelligence also refers to the development of systems capable of performing tasks that would typically require human intelligence, such as problem-solving, decision-making, learning, and natural language processing (Russell & Norvig, 2020). Artificial Intelligence is categorized into narrow AI, which is designed for specific tasks, and general AI, which is still largely theoretical and aims to mimic human cognitive functions across a broad range of activities (Bengio et al., 2017).

In the business sector, AI is reshaping customer service, supply chain management, and marketing strategies. Chatbots and virtual assistants, powered by natural language processing, help businesses provide 24/7 customer support (Shawar & Atwell, 2015). Moreover, Artificial Intelligence driven analytics allow companies to make data informed decisions, optimize operations, and predict market trends, offering a competitive edge (Rimon et al., 2023). Artificial Intelligence systems often rely on large datasets, which can perpetuate biases if the data used is not representative of diverse populations (O'Neil, 2016). Additionally, the growing use of Artificial Intelligence in decision-making processes, such as hiring or criminal justice, calls for transparent and accountable algorithms to ensure fairness and prevent discrimination (Angwin et al., 2016).

Artificial Intelligence has a bright future ahead of it, with advancements predicted to tackle difficult global issues like finance, healthcare access, education and climate change.

Experts in artificial intelligence predicts that artificial intelligence will continue to enhance human applications, leading to more personalized services, smarter cities, and more efficient industries. However, ensuring that these advancements are aligned with societal values and human welfare collaboration between technologists, ethicists, and policymakers will be required (Brynjolfsson & McAfee, 2017).

2.1.6 Artificial Intelligence Technologies

Machine Learning

Machine learning (ML) is a subset of artificial intelligence (AI) that focuses on the development of algorithms and statistical models that enable computer systems to learn and improve from experience without explicit programming (Aggarwal, 2023). It uses data-driven approaches to identify patterns, make decisions, and predict outcomes, making it valuable in various fields, including finance, healthcare, and marketing (Alpaydin, 2020). Allowing systems to learn from data, adapting to new inputs, and carrying out tasks with little assistance from humans is the core concept of machine learning. The three main categories of machine learning are reinforcement learning, unsupervised learning, and supervised learning. Supervised learning relies on labeled data to train models, while unsupervised learning deals with unlabeled data, aiming to find hidden patterns and relationships (James et al., 2013). Reinforcement learning, on the other hand, uses a reward-based system to guide the learning process, optimizing decision-making over time (Sutton & Barto, 2018). The increasing availability of large datasets and advancements in computational power has significantly accelerated the growth and application of ML.

Expert System

According to Jackson (2019), "expert system is a branch of artificial intelligence (AI) designed to replicate the decision-making applications of human experts". These systems consist of a knowledge base and an inference engine, which work together to analyze data and generate recommendations or solutions to complex problems (Isizoh et al., 2023). The knowledge base stores specialized information gathered from domain experts, while the inference engine applies logical rules to derive conclusions, simulating the reasoning process of human experts (Russell & Norvig, 2021).

Expert systems are widely used in fields like medicine, finance, engineering, and customer support, where expert knowledge is essential for accurate decision-making. For example, in the medical field, expert systems can assist in diagnosing diseases and recommending treatments based on patient data (Jackson, 2019). Similarly, in finance, expert system can help evaluate credit risks, detect fraud, and provide investment advice (Goyal et al., 2025).

Regardless of their benefits, expert systems are typically domain-specific and struggle with problems outside their scope of knowledge. Additionally, the development process can be time-consuming and costly due to the need to gather and encode extensive expert knowledge (Sayed, 2021).

Natural Language Processing

Devlin et al. (2019) posited that "Natural Language Processing (NLP) is a field of artificial intelligence (AI) focused on enabling computers to understand, interpret, and generate human language. It combines techniques from linguistics, computer science, and machine learning to process large amounts of natural language data". NLP powers many applications that have become commonplace today and these includes virtual assistants, chatbots, machine translation, and sentiment analysis (Jurafsky & Martin, 2021).

At its core, NLP encompasses a number of activities, including machine translation, named entity recognition, tokenisation, parsing, and part-of-speech tagging. Early approaches to NLP relied heavily on hand-crafted rules and statistical models. Techniques such as word embeddings (e.g., Word2Vec, GloVe) and transformer-based architectures (e.g., BERT, GPT) have dramatically improved the performance of NLP systems (Vaswani et al., 2017; Devlin et al., 2019).

The inherent ambiguity and diversity of human language present a significant difficulty for natural language processing. People frequently employ idioms, slang, and informal language that make interpretation more difficult, and words frequently have several meanings depending on the situation. Moreover, NLP systems must handle different languages, dialects, and cultural nuances to perform effectively across global applications (Cambria & White, 2014).

Large datasets, processing capacity, and continuous advancements in deep learning are what drive NLP's continued rapid growth. Its applications are expanding into fields such as healthcare, law, finance, and education, where automated language understanding can streamline processes and improve decision-making (Chiu & Nichols, 2016).

2.2 Artificial Intelligence applications in Financial Reporting

Some of the applications of Artificial Intelligence used in financial reporting are:

Artificial Intelligence Accounting application

Artificial Intelligence Data Analytic application.

Artificial Intelligence Auditing application.

Artificial Intelligence predictive application

2.2.1 Artificial Intelligence Accounting Application

In recent years, artificial intelligence (AI) has transformed the field of accounting by enhancing efficiency, accuracy, and decision-making in financial processes. AI accounting application refers to the application of machine learning algorithms, natural language processing, robotic process automation (RPA), and predictive analytics to automate, analyze, and improve accounting functions (Kokina & Davenport, 2017). This technological application has become increasingly important as organizations seek to enhance financial transparency and reporting quality while reducing human errors.

One of the major contributions of AI accounting application is the automation of routine accounting tasks. Traditional accounting functions such as data entry, reconciliation, and invoice processing are time-consuming and prone to errors when handled manually. AI-powered accounting systems automate these processes, allowing accountants to focus on higher-value tasks such as financial analysis and strategic planning (Issa et al., 2016). For example, AI-based tools like RPA can process large volumes of financial data at high speed, ensuring efficiency and cost-effectiveness in accounting operations.

Furthermore, AI enhances accuracy and fraud detection in accounting. By analyzing patterns and anomalies in financial data, AI systems can identify irregular transactions that may indicate fraud or errors (Appelbaum et al., 2017). This application improves the reliability of financial reporting by ensuring that inconsistencies are detected in real time. As financial reporting quality is largely dependent on accuracy and reliability, AI accounting application directly contributes to better decision-making by stakeholders.

Additionally, AI provides predictive and prescriptive analytics that support accountants in financial forecasting and planning. Unlike traditional accounting systems, AI can process unstructured and structured data, generating insights for future performance and risk management (Sutton et al., 2016). This analytical application equips organizations with a forward-looking perspective, thereby strengthening strategic financial reporting and enhancing corporate governance.

Notwithstanding the gains of AI accounting application, it also has some shortcomings such as high implementation costs, ethical concerns, and the potential displacement of human labour. Accountants may fear that automation will replace their roles; however, research suggests that AI complements human expertise by handling repetitive tasks while professionals focus on judgment-based and interpretative functions (Kokina & Davenport, 2017). AI therefore should be viewed as a supportive tool that augments rather than replaces human accountants.

In summary, artificial intelligence accounting application is revolutionizing the accounting profession by automating routine processes, improving accuracy, detecting fraud, and enabling predictive analytics. The integration of AI in accounting enhances efficiency, financial reporting quality, and decision-making. As organizations increasingly adopt AI technologies, the accounting profession will continue to evolve toward a more strategic and data-driven role.

2.2.3 Artificial Intelligence Data Analytic Application

Artificial Intelligence (AI)-driven analytics reports represent a transformative shift in the way organizations process, analyze, and interpret data for strategic decision-making. These reports integrate AI techniques such as machine learning (ML), natural language processing (NLP), and predictive modeling to automate data analysis and provide actionable insights in real-time (Duan et al., 2019). Unlike traditional reporting methods that rely heavily on manual data manipulation, AI-driven analytics deliver high-speed, accurate, and contextually relevant information.

One of the key features of AI-driven analytics is predictive and prescriptive analysis. Predictive analytics uses historical data and Machine Learning algorithms to forecast future trends, while prescriptive analytics recommends actionable strategies based on those predictions. Machine Learning offer dashboards that not only show what is happening but also explain why it is happening and suggest what to do next (Wamba-Taguimdje et al., 2020).

AI-driven analytics reports also employ natural language generation (NLG) to translate complex datasets into human-readable narratives. This technology enables non-technical users to understand reports without needing expertise in statistics or programming. Tools like Narrative Science's Quill or Automated Insights' Wordsmith generate written explanations of trends, anomalies, and key metrics directly from data, thus enhancing accessibility and reducing interpretation errors (Kraus et al., 2020).

Furthermore, AI improves the efficiency and accuracy of data reporting by automatically cleaning, integrating, and processing vast amounts of structured and unstructured data. This reduces human error and bias, while significantly speeding up reporting cycles. According to Wang and Hajli (2017), AI's ability to detect data patterns and inconsistencies in real-time enables businesses to make more timely and evidence-based decisions.

In finance and business intelligence, AI-driven analytics reports are used for credit risk assessment, fraud detection, customer segmentation, and performance forecasting. For example, banks use AI-powered analytics to evaluate loan applicants based on patterns in credit behavior, social media activity, and transaction history by providing more holistic and dynamic risk assessments than traditional scoring methods (Bussmann et al., 2021).

However, the deployment of AI-driven reporting is not without challenges. These include issues of data privacy, algorithmic bias, lack of transparency (the "black box" problem), and the need for high-quality data inputs (Rahwan et al., 2019). Additionally, organizations must invest in technical infrastructure and workforce training to fully leverage AI applications.

Summarily AI-driven analytics reports have redefined business intelligence and performance monitoring by offering faster, deeper, and more accurate insights.

2.2.4 Artificial Intelligence Auditing Application

The rapid advancement of technology has significantly impacted the auditing profession, with Artificial Intelligence (AI) emerging as one of the most transformative tools in recent years. AI enables auditors to analyze vast amounts of financial and non-financial data, detect anomalies, and enhance risk assessments with greater accuracy and efficiency than traditional methods. While auditors have long relied on sampling techniques and manual review, AI now allows for the comprehensive examination of entire datasets, thereby improving audit quality and reliability (Onyenahazi, 2025). The adoption of AI is reshaping the role of auditors, shifting their focus from repetitive tasks to strategic decision-making and professional judgment. One of the most significant applications of AI in auditing is anomaly detection. Traditional audits often rely on sample testing, which may overlook irregular transactions. AI algorithms, however, can evaluate entire populations of financial records, identify suspicious patterns, and flag potential fraud with high precision (Ali, 2025). This enhances the auditor's ability to provide reasonable assurance about the financial statements while reducing the risk of oversight.

AI is also revolutionizing document analysis through Natural Language Processing (NLP) and Optical Character Recognition (OCR). Auditors often review contracts, minutes of meetings, and regulatory reports to verify compliance. AI-powered tools can rapidly extract relevant information from these unstructured sources, saving time and increasing audit coverage (Adelakun, 2022). Similarly, predictive analytics driven by AI enables auditors to assess risks by considering macroeconomic data, industry trends, and historical financial behavior, which improves the accuracy of risk-based auditing (Ali, 2025).

Another important application is continuous auditing; unlike traditional audits, which are periodic, AI allows for near real-time monitoring of transactions and processes. This facilitates proactive detection of errors and irregularities rather than retrospective identification (Wolters, 2024). Moreover, AI automation reduces routine tasks such as reconciliations, data entry, and sample selection, enabling auditors to allocate more time to professional judgment and critical analysis (Templafy, 2024).The integration of AI into auditing delivers several benefits. First, it improves efficiency, as large datasets can be analyzed quickly without compromising accuracy (DataSnipper, 2024). Secondly, it enhances audit quality, as AI reduces human error and increases the reliability of findings (Noordin et al., 2022). Thirdly, AI contributes to strategic insight by generating predictive reports and dashboards that provide deeper understanding of organizational risks (Wolters, 2024). Furthermore, firms adopting AI are seen as more innovative and attractive to top talent, giving them a competitive edge in the accounting industry (Javed et al., 2025).

Regardless of the advantages, AI Auditing application is not without challenges. One of the key concerns is data reliability, as AI systems may produce inaccurate results or "hallucinations" if the underlying data is flawed (Forvis, 2024). Additionally, AI lacks ethical reasoning, meaning auditors must still exercise professional skepticism and judgment to build trust with stakeholders (Forvis, 2024). High implementation costs also create barriers, particularly for small and medium-sized audit firms (Bello et al., 2024). Moreover, the absence of standardized regulations governing the use of AI in auditing raises uncertainty about accountability and governance (Obemeata, 2025).

Artificial Intelligence has become a powerful tool in auditing, transforming how auditors conduct data analysis, risk assessment, and fraud detection. While it improves efficiency, accuracy, and continuous monitoring, its adoption also presents challenges related to data reliability, ethics, and regulatory oversight. The role of auditors is not being replaced but redefined, with human judgment remaining crucial in interpreting AI outputs and ensuring the integrity of audit opinions. As the auditing profession continues to evolve, integrating AI responsibly will be key to achieving high-quality, reliable, and trustworthy audits in the digital age.

2.2.5 Artificial Intelligence Predictive Application

Artificial intelligence (AI) has advanced beyond simple automation and rule-based processing to become a critical tool for prediction and decision-making. Predictive application, a major strength of AI, refers to the ability of systems to analyze large volumes of historical and real-time data to forecast future outcomes, patterns, and behaviors (Jordan & Mitchell, 2015). This application has significant implications for business, finance, healthcare, and governance, as it enables organizations to anticipate risks, optimize strategies, and enhance performance.

AI predictive application is grounded in machine learning (ML) and statistical modeling. By training algorithms on large datasets, AI systems can identify complex, non-linear relationships and generate forecasts with higher accuracy than traditional forecasting techniques (Makridakis et al., 2018). For instance, in the financial sector, predictive AI models are used for credit scoring, risk assessment, fraud detection, and stock market forecasting, thereby supporting more reliable decision-making processes (Brynjolfsson & McElheran, 2016). Unlike human intuition, AI prediction is data-driven, scalable, and capable of processing millions of variables simultaneously.

One of the most important applications of AI predictive application lies in risk management. In business contexts, predictive analytics helps organizations anticipate potential defaults, identify customers at risk, and estimate financial losses. Banks and insurance firms, for example, rely on AI-driven predictive models to improve customer profiling, reduce non-performing loans, and strengthen regulatory compliance (Adetunji & Chinonso 2025). This enhances not only operational efficiency but also financial stability and accountability.

Moreover, AI predictive application contributes to innovation in healthcare and public policy. In medicine, predictive models analyze patient data to forecast disease outbreaks, progression, and treatment outcomes, leading to more personalized and preventive healthcare strategies (Esteva et al., 2019). Similarly, governments and development agencies leverage AI prediction to anticipate economic shifts, monitor social risks, and plan for crises such as pandemics or natural disasters (UNESCO, 2021). These applications underscore the transformative role of AI in shaping proactive, rather than reactive, decision-making.

Even with the advantages of AI predictive application, it faces challenges that can undermine its effectiveness. Data quality and availability remains a significant barrier; biased, incomplete, or poor-quality datasets can lead to inaccurate predictions and reinforce systemic inequalities (Barocas et al., 2019). Additionally, the “black-box” nature of some predictive algorithms raises concerns about explainability and accountability, particularly in sensitive sectors such as finance and healthcare. Regulators and stakeholders increasingly demand that AI predictions be transparent and interpretable to ensure trust and fairness in decision-making (Doshi-Velez & Kim, 2017).

2.2.6 Artificial Intelligence Accounting application in relation to Financial Reporting

Accounting application has redefined financial reporting by enhancing accuracy, timeliness, fraud detection, and predictive insights. Its integration aligns with the qualitative characteristics of financial information, thus improving reporting quality and stakeholder confidence. AI accounting application refers to the use of intelligent systems and algorithms to process financial data, detect anomalies, and generate insights for decision-making (Issa et al., 2016). In financial reporting, AI plays a pivotal role in improving the quality of information provided to stakeholders by ensuring compliance with accounting standards, reducing human error, and enabling predictive analysis of financial outcomes.

One of the core contributions of AI accounting application to financial reporting lies in automation. Traditionally, financial reporting involved manual data entry, reconciliation, and adjustments, which were often prone to errors and inconsistencies. AI systems can automate these repetitive processes, ensuring that financial data is processed in real time and with greater accuracy (Deloitte, 2019). This automation enhances the timeliness and reliability of financial reports, which are critical qualitative characteristics of financial reporting as outlined by the International Accounting Standards Board (IASB).

In addition to automation, AI improves the detection of irregularities and fraud within financial reporting. Machine learning algorithms can analyze large datasets to identify unusual patterns, thereby strengthening the transparency and integrity of financial statements (Moll & Yigitbasioglu, 2019). For instance, AI-powered anomaly detection tools are capable of identifying inconsistencies in transaction records that may not be apparent to human auditors. This application not only reduces the risk of fraudulent financial reporting but also enhances stakeholders' confidence in financial disclosures.

AI accounting application enhances the decision-usefulness of financial reports through predictive analytics. By leveraging historical financial data, AI systems can forecast future financial performance, assess risks, and provide management with forward-looking insights (Kokina & Davenport, 2017). This predictive functionality transforms financial reporting from a backward-looking activity into a strategic tool for planning and decision-making. Consequently, stakeholders are provided with more relevant and insightful financial information, aligning with the qualitative characteristic of relevance as prescribed by the IASB.

The adoption of AI in financial reporting has many challenges like ethical concerns, data privacy issues and the risk of overreliance on AI systems (Appelbaum et al., 2017). Additionally, the complexity of AI models can make it difficult for managers, auditors, and regulators to fully understand how outputs are generated, potentially reducing transparency.

2.2.7 Artificial Intelligence Data Analytics application in relation to Financial Reporting

The integration of artificial intelligence (AI) into financial analytics has transformed the way organizations prepare, analyze, and present financial reports. AI-driven analytic reporting involves the application of machine learning (ML), natural language processing (NLP), and predictive modeling to interpret large volumes of financial data, detect trends, and generate actionable insights in real time (Appelbaum et al., 2017). This transition from static, historical financial statements toward dynamic analytics-based reporting, has improved decision-making, enhanced accuracy, and supported regulatory compliance.

AI analytic reporting uses advanced algorithms to automate data collection, perform variance analysis, forecast performance, and visualize financial metrics in real time (Luo et al., 2018). Tools such as IBM Cognos Analytics, Microsoft Power BI with AI integration, and Tableau

AI can process structured and unstructured data from multiple systems to provide continuous monitoring of business performance.

For instance, AI systems can predict cash flow positions based on historical patterns, seasonality, and external economic indicators, enabling proactive adjustments towards operations (Kokina & Davenport, 2017). These tools also incorporate anomaly detection to flag irregular transactions before they impact official reports (Issa et al., 2016).

AI-powered analytic platforms reduce human error by automating complex calculations and consolidations. Machine learning models continually refine predictions as new data is fed into the system, enhancing the reliability of reported figures (Moll & Yigitbasioglu, 2019). Traditional financial reports are retrospective, often lagging behind operational realities. AI analytics enables real-time reporting through dynamic dashboards, allowing decision-makers to respond to market and operational shifts promptly (Appelbaum et al., 2017).

Predictive analytics supported by AI provides more accurate forecasting for revenue, expenses, and profitability, improving budgeting and strategic planning processes (Zhang et al., 2020). AI can automatically apply relevant accounting standards (e.g., IFRS or GAAP) to transaction classifications, and maintain detailed audit trails for compliance reviews (Luo et al., 2018).

AI-driven analytics leverage advanced machine learning algorithms, natural language processing (NLP), and big data techniques to process vast amounts of structured and unstructured financial data. Unlike traditional reporting, which often presents static historical figures, AI-powered analytics provide dynamic, real-time interpretations and predictive insights that clarify the underlying drivers of financial outcomes (Davenport & Ronanki, 2018). This application supports transparency by making complex financial data more understandable and accessible to stakeholders.

For example, AI-based tools can analyze footnotes and management discussion and analysis (MD&A) sections using NLP to detect inconsistencies or vague language that may obscure the true financial position of a company (Issa et al., 2016). By highlighting these potential issues, AI facilitates more transparent disclosures and encourages management to improve the clarity and completeness of their reports. This function is crucial, given that ambiguous language and selective disclosure have historically been challenges to transparency.

Additionally, AI-driven analytics can detect anomalies or fraudulent patterns that may otherwise go unnoticed in voluminous datasets. Systems such as KPMG's Clara platform utilize AI to perform continuous auditing and real-time risk assessments, automatically flagging transactions or balances that deviate from expected patterns (KPMG, 2020). This proactive identification of irregularities promotes transparency by ensuring that financial statements reflect true and fair views, thereby reducing the risk of misstatements and earnings management.

Also, AI enables enhanced visualization of financial data through interactive dashboards and scenario analyses, allowing stakeholders including investors, regulators, and auditors to explore data at granular levels and verify assumptions underlying reported figures. For instance, IBM's Watson Analytics offers intuitive interfaces where users can drill down into financial metrics, uncover trends, and validate key performance indicators (KPIs) (IBM, 2019). This level of engagement with financial information demystifies complex reports and supports transparent communication.

However, the deployment of AI in financial reporting must be accompanied by robust governance frameworks to mitigate risks related to data privacy, algorithmic bias, and model interpretability (Ransbotham et al., 2018). Transparency extends not only to the financial data but also to the AI processes themselves; stakeholders therefore need assurance that AI-driven analytics are reliable and free from manipulation.

2.2.8 Artificial Intelligence Auditing Application in relation to Financial Reporting

Financial reporting is a critical aspect of corporate governance, providing stakeholders with reliable information for decision-making. The integrity of financial reports is largely safeguarded through auditing, which ensures compliance with accounting standards and detects potential misstatements or fraud. With the rise of digital transformation, Artificial Intelligence (AI) has become a game-changer in auditing by enhancing the quality, reliability, and timeliness of financial reporting. Unlike traditional audit methods that often rely on sampling, AI tools can analyze entire datasets, offering auditors deeper insights into financial records (Thomson, 2025). As a result, AI is reshaping the auditing process and its relationship with financial reporting by improving accuracy, transparency, and assurance.

One of the major contributions of AI in auditing is improving the accuracy of financial reporting. Traditional audits often leave room for error due to human limitations and reliance on samples. AI systems can process massive volumes of structured and unstructured financial data, ensuring that anomalies, duplications, or irregular transactions are identified promptly (Trullion, 2024). For example, AI-driven anomaly detection tools can flag unusual journal entries that may indicate fraudulent reporting, thereby reducing the risk of material misstatements. This strengthens the credibility of financial statements and enhances stakeholder confidence.

AI also contributes to the timeliness of financial reporting by enabling continuous auditing. Instead of waiting for year-end or quarterly reviews, AI tools can monitor financial transactions in real time, ensuring that discrepancies are addressed as they occur (Wolters, 2024). Continuous auditing facilitates more up-to-date financial information, which is critical for investors and regulators who rely on timely disclosures. Moreover, by automating repetitive audit procedures, AI allows auditors to complete their work faster, expediting the release of audited financial statements (Templafy, 2024).

Financial reporting requires not only accuracy and timeliness but also transparency and compliance with international accounting standards. AI-powered Natural Language Processing (NLP) can analyze contracts, regulatory filings, and disclosures to ensure compliance with IFRS or GAAP requirements (Codewave, 2024). For instance, AI can automatically compare company disclosures with industry benchmarks to identify gaps or inconsistencies. By doing so, AI enhances the auditor's ability to verify whether financial statements fairly present an organization's financial position. Furthermore, predictive analytics can help assess potential reporting risks by analyzing historical and market data, enabling auditors to anticipate areas of non-compliance (Thomson, 2025).

The use of AI in auditing directly improves the quality of assurance provided on financial reports. AI reduces the reliance on judgmental sampling by enabling full-population testing, which increases audit coverage and reduces the likelihood of oversight (Noordin et al., 2022). Additionally, advanced machine learning models can detect subtle financial irregularities that traditional audits may miss, thereby enhancing the robustness of audit opinions. This contributes to the overall credibility of financial reports and promotes stakeholder trust in the financial reporting process (Alhazmi et al., 2025).

Integrating AI into auditing for financial reporting is not without issues. One key problem is data reliability, as AI outputs are only as reliable as the data they process. If financial data is incomplete or biased, AI models may produce misleading results (Forvis, 2024). Another concern is the ethical dimension that AI lacks professional skepticism and judgment, which are central to auditing. Therefore, human auditors remain indispensable for interpreting AI-generated insights in the context of financial reporting (Adelakun, 2022). Finally, the lack of standardized regulations regarding AI use in audits creates uncertainty about accountability, particularly when AI-generated results are used to support financial statement assurance (Apooyin, 2025).

Artificial Intelligence is revolutionizing auditing and redefining its relationship with financial reporting. By improving accuracy, timeliness, compliance, and transparency, AI enhances the overall quality of financial reports and increases stakeholder confidence. However, challenges such as data reliability, ethical concerns, and regulatory gaps mean that AI should be viewed as a complement rather than a replacement for human auditors.

2.2.9 Artificial Intelligence Predictive Application in Relation to Financial Reporting

The increasing complexity of global financial environments has placed pressure on organizations to provide accurate, timely, and transparent financial reports. Financial reporting quality is critical to investor confidence, regulatory compliance, and effective decision-making. Artificial intelligence (AI), particularly through its predictive application, is transforming financial reporting by enabling firms to anticipate risks, forecast outcomes, and enhance the overall reliability of accounting information. Predictive application refers to AI's ability to analyze structured and unstructured data using machine learning algorithms and statistical models to forecast future financial events with higher precision (Jordan & Mitchell, 2015). When applied to financial reporting, this application improves relevance, timeliness, and decision usefulness of reports.

AI predictive application enhances financial reporting primarily through accurate forecasting of financial performance and risks. Traditional financial reporting systems rely heavily on historical data, which, while useful, may not adequately capture emerging risks or trends. AI predictive models analyze patterns in large datasets, generating forward-looking insights such as revenue projections, credit losses, and cash flow forecasts (Makridakis et al., 2018). For example, the use of predictive analytics in accounting allows firms to anticipate non-performing loans, estimate provisions, and improve compliance with International Financial Reporting Standards (IFRS) requirements, particularly those related to expected credit loss models (Jan & Emmeli 2017). This enhances the reliability and completeness of financial statements.

Another significant contribution of AI predictive application is in fraud detection and anomaly identification. By analyzing patterns in transactional and financial data, predictive algorithms can flag unusual entries that may signal fraud or material misstatement (Appelbaum et al., 2017). This reduces the risk of errors and misrepresentation, thereby increasing the credibility of financial reports. Furthermore, predictive AI models can evaluate the likelihood of financial restatements by identifying early warning signals in accounting data, providing assurance to auditors and regulators about the quality of disclosures (Issa et al., 2016).

Predictive AI also contributes to enhancing the timeliness of financial reporting. Organizations traditionally prepare reports at fixed intervals, but predictive systems can generate continuous forecasts, allowing management and stakeholders to access near real-time financial insights (Brynjolfsson & McElheran, 2016). This continuous monitoring reduces reporting lags, aligns disclosures more closely with current realities, and enhances decision-making based on up-to-date information. Consequently, predictive application supports the International Accounting Standards Board's (IASB) enhancing qualitative characteristics of timeliness and relevance in financial reporting.

The use of AI predictive application in financial reporting is not problem free. Data integrity, quality, and accessibility are major concerns, as biased or incomplete data can lead to misleading forecasts (Barocas et al., 2019). Furthermore, predictive models often operate as "black boxes," making it difficult for auditors, regulators, and managers to interpret how outcomes are generated (Doshi-Velez & Kim, 2017). This lack of transparency raises questions about accountability and trust in financial reporting. Ethical concerns also arise when predictive systems inadvertently perpetuate bias, which can compromise fairness and stakeholder confidence.

2.2.10 Artificial Intelligence Accounting application and Financial Reporting Quality in Nigeria Banks

The rapid diffusion of artificial intelligence (AI) across the global financial sector has created new applications for accounting systems that directly affect financial reporting quality. In Nigeria, banks which operate in a fast-changing, heavily regulated environment and increasingly large volumes of digital transactions AI accounting applications (including automation, machine learning, natural language processing, and anomaly detection) have the potential to improve timeliness, accuracy, completeness, and transparency of their financial reports. AI accounting application can be understood as the ability of accounting systems to ingest, process, analyze, and learn from large and varied financial data inputs in order to automate routine tasks, detect anomalies, and produce decision-useful outputs (Kokina & Davenport, 2017; Deloitte, n.d.). In the context of banks, these applications include automated transaction classification, real-time reconciliation, predictive provisioning, automated audit trails, and machine-driven disclosures that transform raw transactional data into higher-quality financial information (KPMG, 2025). By reducing manual processing and human error, AI can strengthen two fundamental qualities of financial reporting and they are, reliability and accuracy. Empirical evidence from studies of Nigerian firms and the banking sector shows a positive relationship between digitalization/AI adoption and improved reporting metrics (Oduwole & Fatogun, 2023).

One concrete area where AI improves reporting quality is error reduction in transaction processing and reconciliations. Banks process millions of small value and high-value transactions daily; manual reconciliation is time-consuming and error-prone. AI-driven robotic process automation (RPA) and rule-based engines can reconcile transactions faster and flag exceptions for human review, reducing misstatements and late adjustments in financial statements (Deloitte, n.d., KPMG, 2025). Several recent empirical studies conducted in Nigeria report that automation and intelligent agents have statistically significant positive effects on accounting practice and on the perceived quality of financial statements (Oduwole & Fatogun, 2023).

AI also enhances fraud detection and internal control assurance which is a key determinant of reporting credibility. Machine learning models trained on historical transaction patterns can identify anomalous behavior, suspicious transfers, and potential money-laundering indicators much earlier than rule-based systems alone (CBN, 2025). Improved anomaly detection reduces the risk of material misstatement arising from fraud and strengthens the audit trail, thereby increasing stakeholder confidence in bank financial reports (Alaba, 2025). Recognizing this, Nigeria's apex regulator has been developing guidance for automated AML solutions that explicitly encourage AI-enabled systems as part of a baseline standard for financial institutions (Central Bank of Nigeria [CBN], 2025).

Beyond detection and automation, AI contributes to forward-looking elements of reporting such as provisioning and risk disclosures. Predictive analytics and machine learning enable banks to model credit risk dynamics and expected credit loss (ECL) with richer, near-real-time inputs improving the timeliness and relevance of provisioning estimates disclosed in financial statements (KPMG, 2025). Studies of big data and reporting quality in Nigeria find that the velocity and variety of data are available to firms, when properly harnessed, correlate with improved disclosure completeness and fewer restatements (Onyeka, 2025).

However, there are sector-specific limitations and risks that can blunt AI's positive impact on reporting quality in Nigerian banks. First, data quality and integration remain problematic. Legacy core-banking systems, fragmented data siloes, and inconsistent accounting classifications make it difficult for AI models to produce reliable outputs without substantial data-cleansing and governance investment (Deloitte, n.d; Oduwole & Fatogun, 2023). Secondly, skills and change management are issues: effective deployment of AI requires personnel skilled in data science, accounting, and governance competencies that are still emerging in many Nigerian banks (KPMG, 2023). Thirdly, model transparency and explainability are essential for auditors and regulators; “black-box” AI models can create challenges for external audit and regulatory oversight unless accompanied by robust model-risk frameworks (CBN, 2025).

Regulatory and governance responses are therefore critical. Nigerian regulators that have signaled an intent to accommodate and supervise AI adoption like the CBN’s exposure draft on baseline standards for automated AML solutions is one example but banks must also establish internal AI governance, data stewardship, and model validation processes to ensure reliable outputs are produced and disclosed (CBN, 2025). Academic and practitioner studies in Nigeria recommend that banks adopt phased implementation approaches that pair automation with strengthened internal controls and auditor involvement to preserve reporting quality during transition (Oduwole & Fatogun, 2023).

2.2.11 Artificial Intelligence Data Analytic Application and Financial Reporting Quality in Nigeria Banks

Artificial intelligence (AI) data analytics is increasingly shaping financial reporting processes in the global banking sector, including Nigeria. Data analytics refers to the systematic computational analysis of data, and when combined with AI techniques such as machine learning (ML) and natural language processing (NLP), enables banks to extract meaningful insights from vast datasets for decision-making and regulatory compliance. For Nigerian banks, which operate under International Financial Reporting Standards (IFRS) and the Central Bank of Nigeria’s (CBN) regulatory framework, AI-powered analytics directly affects the quality of financial reporting. Financial reporting quality is defined by characteristics such as relevance, faithful representation, comparability, verifiability, and timeliness (IFRS Foundation, 2018).

AI data analytics improves the relevance of financial reports by enabling predictive modelling and trend analysis. For instance, banks can apply machine learning to customer transaction data to forecast credit risk and detect early signs of default. These insights feed into forward-looking impairment models under IFRS 9, thereby ensuring that reported financial information reflects current and expected economic conditions (BIS, 2017; CBN, 2018). This predictive ability ensures that financial reports are not only historical records but also decision-useful tools.

Financial reporting must faithfully represent the underlying transactions and conditions of an organisation. AI data analytics enhances accuracy by identifying anomalies, detecting fraud, and reconciling large volumes of transactions in real time. For example, anomaly-detection algorithms can highlight suspicious patterns that may distort reported income or expenses. This reduces the incidence of misstatements and improves the reliability of reported figures (Financial Stability Board [FSB], 2024).

AI-driven analytics can enforce standardised classification of accounts and automate the preparation of disclosures. Nigerian banks, many of which operate across multiple subsidiaries, benefit from consistent consolidation practices driven by AI tools. By ensuring that similar transactions are treated consistently across reporting entities, AI analytics supports comparability which is one of the key enhancing characteristics of financial reporting (IFRS Foundation, 2018).

Traditional financial reporting processes in Nigerian banks often involve manual reconciliations and delayed adjustments. AI data analytics reduces the financial close cycle by processing high-volume data streams quickly and generating reports in near real-time.

Timely reporting improves regulatory compliance, particularly with the CBN's strict deadlines for financial statement submissions (CBN, 2023).

Verifiability requires that financial information can be independently confirmed. AI systems enhance this through automated data lineage tracking and audit trails that record how data moves from source systems into financial statements. This transparency allows external auditors and regulators to verify reported numbers, thereby improving confidence in Nigerian banks' disclosures (FSB, 2024).

The Nigeria regulatory and institutional landscape significantly influences how AI data analytics is deployed in financial reporting. For example IFRS 9 implementation, CBN Corporate Governance Guidelines (2023), Data Protection and Cybersecurity and Sustainability Reporting**.** Nigeria banks adopted IFRS 9 in 2018, with transitional arrangements provided by the CBN due to the impact of forward-looking expected credit loss (ECL) provisioning. AI analytics plays a key role in integrating macroeconomic variables into ECL models (CBN, 2018).

CBN Corporate Governance Guidelines (2023) emphasize board oversight of technology and internal controls, requiring banks to establish robust governance frameworks around AI and data analytics (CBN, 2023). Data Protection and Cybersecurity is very crucial in data analytics**.** The Nigeria Data Protection Act (2023) and the CBN Risk-Based Cybersecurity Framework (2024) impose standards for lawful data processing, confidentiality, and cyber risk management issues that are critical when financial data is processed by AI systems (Nigeria Data Protection Act, 2023; CBN, 2024).

Sustainability Reporting is another important factor in artificial intelligence data analytics application**.** With Nigeria's roadmap to adopt IFRS Sustainability Disclosure Standards, banks are expected to use AI analytics for environmental, social and governance (ESG) data collection and reporting, ensuring comparability and relevance of sustainability disclosures

(FRCN, 2024). The benefits of AI data analytics include more relevant and predictive reporting, fewer manual errors, stronger compliance monitoring, and enhanced timeliness. However, risks include data bias that could distort results and cybersecurity vulnerabilities that may undermine the integrity of financial data (FSB, 2024).

AI data analytic applications significantly enhance financial reporting quality in Nigerian banks by improving timeliness, accuracy, relevance, and comparability of reports. Nonetheless, these benefits depend on robust governance, explainability of AI models, and adherence to Nigerian regulatory frameworks on corporate governance, data protection, and cybersecurity. To fully realise AI's potential, Nigerian banks must balance innovation with accountability ensuring that financial reporting remains reliable, transparent, and decision-useful.

2.2.12 Artificial Intelligence Auditing Application and Financial Reporting Quality in Nigeria Banks

Artificial intelligence (AI) is revolutionizing the auditing landscape by automating processes, detecting anomalies, and enhancing compliance monitoring in financial institutions. In Nigeria, where banks play a pivotal role in financial intermediation, the integration of AI into auditing functions is critical to the quality of financial reporting. Financial reporting quality is determined by its relevance, faithful representation, comparability, verifiability, and timeliness (IFRS Foundation, 2018). With Nigerian banks operating under International Financial Reporting Standards (IFRS) and strict oversight from the Central Bank of Nigeria (CBN), AI auditing applications have the potential to strengthen the reliability and transparency of financial statements. The benefits of AI auditing in Nigerian banks include improved fraud detection, more reliable reporting, and enhanced timeliness of financial information. However, challenges like model opacity makes it difficult for auditors to explain AI-driven judgments; overreliance on AI without professional skepticism can lead to oversight failures; and cybersecurity risks may compromise sensitive audit evidence (FSB, 2024). AI auditing applications hold significant promise for improving financial reporting quality in Nigerian banks.AI strengthens trust in financial information for regulators, investors, and other stakeholders by enhancing faithful representation, reliability, timeliness, and verifiability. However, Nigerian banks must pair AI adoption with strong governance, ethical oversight, and compliance with CBN and data protection regulations to ensure that financial reporting remains both technologically advanced and institutionally credible.

Traditional auditing methods rely heavily on sampling techniques, which may miss significant misstatements. AI auditing tools, however, can perform full-population testing of financial transactions, ensuring that reported figures faithfully represent underlying events (Kokina & Davenport, 2017). For Nigerian banks that process millions of daily transactions, this automation will improve audit assurance and minimizes undetected errors in financial reporting.

Fraudulent practices, such as insider collusion and unauthorized loan approvals, remain a challenge in Nigeria's banking sector. AI auditing tools, particularly those using machine learning, can detect irregular patterns and flag suspicious activities in real-time (FSB, 2024). This strengthens the reliability of financial reports by reducing the likelihood of material misstatements due to fraud.

AI enables continuous auditing by monitoring financial transactions and controls in real-time rather than relying solely on year-end reviews. This application ensures that Nigerian banks can identify and correct misstatements promptly, improving the timeliness of financial reports submitted to regulators like the CBN (Appelbaum et al., 2017).

Risk-based auditing is enhanced through AI's ability to analyze complex datasets, such as credit risk exposures, liquidity trends, and macroeconomic indicators. By identifying high-risk areas for auditors to focus on, AI ensures that financial reporting remains relevant to decision-makers and regulators in Nigeria's dynamic financial environment (BIS, 2017).

AI systems create robust data lineage and audit trails that document every stage of financial data processing. This improves the verifiability of Nigerian banks' financial reports, as auditors and regulators can trace how transactions were classified and consolidated into final financial statements (FSB, 2024).

However the role of AI auditing in Nigeria must be considered alongside regulatory frameworks and institutional practices such as; CBN Corporate Governance Guidelines (2023).These guidelines require banks' audit committees to strengthen oversight of technology-driven audit processes, ensuring compliance with ethical and professional standards (CBN, 2023). Another practice is the aspect of Data Protection and Cybersecurity**.** The Nigeria Data Protection Act (2023) and the CBN's Risk-Based Cybersecurity Framework (2024) impose legal requirements for safeguarding financial data processed by AI auditing systems (Nigeria Data Protection Act, 2023; CBN, 2024). Lastly is the Adoption of IFRS**.** With IFRS 9's forward-looking expected credit loss (ECL) model, Nigerian banks rely on AI-assisted audit analytics to verify assumptions and models used in impairment reporting (CBN, 2018).

2.2.13 Artificial Intelligence Predictive Application and Financial Reporting Quality in Nigeria Banks

The banking sector in Nigeria has increasingly embraced technological innovation to improve operational efficiency and enhance financial reporting practices. Among these innovations, artificial intelligence (AI) has emerged as a transformative tool with predictive application, enabling banks to generate forward-looking insights from large volumes of financial and non-financial data. Predictive AI refers to the use of machine learning algorithms, data analytics, and pattern recognition to forecast future financial trends, assess risks, and enhance decision-making (Kokina & Davenport, 2017). In Nigerian banks, AI's predictive application holds significant potential for improving financial reporting quality by enhancing relevance, reliability, comparability, and timeliness.

One key contribution of AI predictive application to financial reporting quality is its ability to enhance relevance by providing forward-looking insights. Traditional financial reports are largely historical in nature, focusing on past transactions and performance. However, Nigeria banks are now leveraging predictive AI tools to forecast credit risks, loan defaults, and market volatility (Olayinka & Olaoye, 2021). These predictive insights make financial reports more decision-useful to stakeholders, including investors, regulators, and management, by ensuring that disclosed information reflects both current realities and future expectations.

Furthermore, AI predictive application improves the reliability of financial reporting in Nigerian banks. Predictive models can analyze vast datasets with greater accuracy than manual methods, thereby minimizing human errors in estimations and provisions (Moll & Yigitbasioglu, 2019). For instance, predictive analytics can assist in provisioning for non-performing loans by assessing borrower behaviour patterns and economic indicators. This reduces bias and subjectivity in reporting, ensuring that financial statements fairly represent the bank's financial position.

The predictive application of AI also strengthens timeliness, another essential characteristic of high-quality financial reporting. In the Nigerian banking industry, delays in financial disclosure have often been linked to inefficiencies in data collection and manual analysis (Uwuigbe et al., 2019). AI systems enable real-time monitoring of transactions and immediate generation of predictive reports, thus allowing banks to meet regulatory deadlines and provide timely information to stakeholders. Timely financial reporting not only fosters compliance with the Central Bank of Nigeria's (CBN) guidelines but also builds trust among investors.

Additionally, predictive AI contributes to comparability by standardizing financial forecasting models across banks. Nigerian banks operate in a highly volatile macroeconomic environment, where exchange rate fluctuations, inflation, and regulatory changes impact financial performance. By adopting predictive algorithms, banks can apply consistent models in estimating future performance, thereby ensuring that financial information is comparable across institutions (Olowolaju & Ogunlade, 2022). This comparability enhances transparency and supports stakeholders in making informed investment decisions.

Regardless, issues still exist in the application of AI predictive application in Nigerian banks' financial reporting. Problems such as inadequate technological infrastructure, lack of skilled personnel, and data quality constraints hinder the effective deployment of AI (Adegbie et al., 2020). Moreover, the complexity of predictive algorithms may reduce transparency, making it difficult for regulators and auditors to fully understand the basis of financial forecasts. To address these challenges, Nigerian banks must invest in AI talent development, ensure data integrity, and establish robust governance frameworks to regulate the use of AI in financial reporting.

2.3 Empirical Review

Arefeh (2024) examined the impact of accounting software on enhancing the accuracy and timeliness of financial reports. The study aimed to examine the impact of using accounting software on improving the accuracy and timeliness of financial reports. This research was applied in nature and conducted using a descriptive-survey method with a quantitative approach. The statistical population consisted of accountants and financial experts working in private companies in Tehran, selected through simple random sampling. The data collection tool was a researcher-made questionnaire based on theoretical literature and prior research, including demographic items and statements measuring the variables using a Likert scale. The independent variable was the use of accounting software, assessed through three dimensions, while the dependent variables were the accuracy and timeliness of financial reports. The validity and reliability of the instrument were confirmed by expert review and statistical tests. Data were analyzed using SmartPLS 4 software and the structural equation modeling method. Both the measurement and structural models of the study were evaluated. The results indicated that the use of accounting software has a positive and significant effect on the accuracy and timeliness of financial reports. The measurement instrument demonstrated satisfactory reliability and validity. Path coefficients revealed that accounting software directly influences both the accuracy and timeliness of reports. Furthermore, the model showed a good fit, and accounting software] explained approximately 22.1% and 15.2% of the variance in accuracy and timeliness, respectively. The use of accounting software plays an effective role in enhancing the quality of financial reporting. This impact is particularly evident in two key aspects: the accuracy of financial information and the scheduling of report preparation and presentation.

Pandey and Rana (2024) examined automatic financial report using accounting software based on artificial intelligence. The paper explored the role of AI in accounting for financial reporting, auditing, and financial decision-making. AI played a significant role in accounting through data analytics, algorithms, automation, etc., but it also presents certain difficulties. The study employed a cross-sectional survey research methodology with a standardized questionnaire to collect primary data. To analyse the collected data, both descriptive and inferential statistics were applied. The study employed a cross-sectional survey research methodology with a standardised questionnaire to collect primary data. To analyse the collected data, both descriptive and inferential statistics were applied. According to the study's findings, accounting software efficiently gathers and analyses data and information to generate superior company reports. According to the study, accounting software should be easier to use because it gives businesses a simpler way to handle and process financial reporting processes.

Shah (2025) explored the influence of artificial intelligence (AI) adoption on the timeliness of financial reporting among publicly listed firms. Leveraging multiple regression analysis, the research investigates whether the integration of AI technologies enhances the speed, efficiency, and responsiveness of corporate financial disclosures. By analyzing empirical data across diverse industries, the study seeks to determine the extent to which AI-driven automation and data processing applications contribute to reducing reporting delays and improving overall transparency. The findings are expected to offer valuable insights into the relationship between digital transformation and reporting quality, with implications for regulators, investors, and corporate decision-makers aiming to strengthen corporate governance and stakeholder trust in the era of intelligent automation.

Al-Obaidy (2024) investigated on developing an accounting information system based on Artificial Intelligence to improve the quality of accounting information and the decision making process. This quantitative study aimed to enhance accounting information quality by developing an AI-based accounting information system and examining its impact on the decision-making process. The research utilized questionnaires to gather opinions from accountants at Rafidain Bank, Iraq, and analyzed the data using SPSS. Findings reveal that modern AI technologies significantly enhance accounting data accuracy, with a 90% success rate in detecting and correcting errors. Additionally, AI technology accelerates financial reporting, reducing the average response time to 250 milliseconds, thereby saving time and effort in accounting processes. This study is pioneering in its comprehensive evaluation of AI's role in improving accounting data accuracy and operational efficiency within financial institutions. The research underscores the importance of upgrading device and data processing infrastructure to maximize the performance of AI-based accounting systems. The findings suggest that integrating contemporary AI technology in accounting can streamline operations, save accountants time, and boost the overall efficiency of financial and accounting institutions.

Wilson-Oshilim and Efedhoma, (2024) explored the impact of Artificial Intelligence (AI) on financial reporting accuracy and efficiency among Nigerian companies across various sectors. This research addresses existing gaps by examining the influence of AI-driven technologies such as machine learning, natural language processing, and robotic process automation on improving financial reporting processes. Utilizing a descriptive survey research design and quantitative analysis, the structured questionnaire were distributed to a population of 317 respondents comprising finance professionals, data scientists, and decision-makers within organizations actively implementing AI in financial reporting. The sample size of 100 respondents was purposively selected based on clarity of response from the respondents. The findings indicate that AI has a significant positive impact on both accuracy and efficiency in financial reporting. Specifically, the integration of AI tools enhances the precision of financial data reporting and improves operational efficiency. AI-based automation reduces the likelihood of human error and enables faster data processing, resulting in more reliable and timely financial reports. The study recommends that organizations invest in AI technologies to maintain competitiveness and suggests implementing oversight mechanisms to ensure AI-driven reporting aligns with regulatory standards.

Shaban and Omoush (2025) examined the impact of AI-driven financial transparency on corporate governance and regulatory reform, focusing on Jordan. It utilized a stratified random sampling approach. Data were collected from 564 corporate professionals across key economic sectors. Statistical analyses, including structural equation modeling (SEM) and multiple regression analysis, reveal that AI adoption significantly enhances corporate governance effectiveness (R^2 = 0.582), improves risk management (R^2 = 0.502), and increases stakeholder engagement (R^2 = 0.681). AI also facilitates regulatory compliance by automating monitoring processes and reducing human errors in financial disclosures. However, challenges such as bias in AI algorithms, data privacy concerns, and the need for regulatory adaptation persist. These findings contribute to the body of knowledge on AI-driven governance and provide insights for policymakers and corporate leaders.

Thanasa et al. (2025) examined the enhancing of transparency and efficiency in Auditing and regulatory compliance with disruptive technologies. The paper explored the transformative impact of digital tools on financial reporting, focusing on how advancements in technologies such as blockchain, artificial intelligence (AI), and data analytics have revolutionized the way financial data is managed, reported, and audited. These tools enhance data integration, accuracy, and transparency, while streamlining the auditing process through automation and real-time analysis. The paper also addresses the growing importance of data visualization for better stakeholder engagement and predictive insights. Alongside the benefits, the challenges of adopting these technologies including cybersecurity risks, skill gaps, and ethical concerns were discussed. Looking forward, the paper suggests future directions such as wider blockchain adoption, AI-driven forecasting, and the development of advanced cybersecurity measures. Ultimately, the integration of digital tools promises a more efficient, transparent, and forward-looking financial reporting landscape, but it requires organizations to stay adaptable and proactive in addressing emerging risks and compliance requirements.

Aldemir and Uysal (2025) examined Artificial Intelligence for financial accountability and governance in the public sector, strategic opportunities and challenges. The study investigated the transformative capacity of artificial intelligence (AI) in improving financial accountability and governance in the public sector. The study aims to explore the strategic potential and constraints of AI integration, especially as fiscal systems become more complex and public expectations for transparency increase. This study employs a qualitative case study methodology to analyze three countries, which are Estonia, Singapore, and Finland. These countries are renowned for their innovative use of AI in public administration. The data collection tools included an extensive review of the literature, governmental publications, case studies, and public feedback. The study reveals that AI-driven solutions such as predictive analytics, fraud detection systems, and automated reporting significantly improve operational efficiency, transparency, and decision making. However, challenges such as algorithmic bias, data privacy issues, and the need for strong ethical guidelines still exist, and these could hinder the equitable use of AI. The study emphasizes the importance of aligning technological progress with democratic values and ethical governance by addressing these problems. The study also enhances the dialog around AI's role in public administration. It provides practical recommendations for policymakers who seek to use AI wisely to promote public trust, improve efficiency, and ensure accountability in governance. Future research should focus on enhancing ethical frameworks and investigating scalable solutions to overcome the social and technical challenges of AI integration.

Unuesiri and Adejuwon (2024) investigated on the effect of Artificial Intelligence Expert System in the Financial Performance of Deposit Money Banks in Nigeria. The study analysed the secondary data of selected DMBs for the period 2015 -2023 (9 years). The data were sourced from the Annual Reports of the DMBs, the Central Bank of Nigeria (CBN) Statistical Bulletin and World Development Indicators to establish cause-effect relationships between the variables. Population of the study was the 27 DMBs in Nigeria as at 31st July, 2023, while the sample size was five (5) DMBs (Access Bank, Zenith Bank, UBA, First Bank and GT Bank). The sampling technique used was the non-probability convenience sampling method chosen based on the availability of the financial statements of the DMBs for the period under study. The study employed Error Correction Model (ECM) for time series regression to analyse equilibrium relationships in short run and long run behaviours. The findings showed that the resultant coefficients were positive and significant both during pre-Expert System adoption (coefficient = $1.25668<0.05$) and 1.75328, $p<0.05$ for post-Expert System adoption respectively. The null hypothesis was therefore rejected and we accepted the alternate hypothesis to conclude that the deployment of AI Expert System impacted positively and significantly on the financial performance of DMBs in Nigeria. Based on the findings, we recommend that there should be strategic and realistic investment in AI Expert Systems by the DMBs to improve their financial performance. Oduwole 2023 critically examined the impact of artificial intelligence on accounting practice in the Nigerian banking industry. To attain the objectives of the study, a regression and correction model comprising independent variables (automation process, expert system, and intelligent agent) and dependent variables (accounting practice) was specified for the study. The data for this study were obtained from a primary source where a survey was carried out on banking industries in Nigeria; 133 respondents were chosen as the sample size, of which 128 were returned. The data were analyzed using regression method of inferential statistics to test the significance of hypotheses using the t-statistics of coefficient with the generated p-values. The findings revealed that all three variables (automation process, expect system, and intelligent agent) have a significant effect on accounting practice in deposit money banks (DMBs) industries in Nigeria. Therefore, the conclusion is that artificial intelligence enhances accounting practice in selected DMBs industries in Nigeria. It was recommended that banking industries and accountants, by improving their knowledge of artificial intelligence and enhancing their performance, will be able to eliminate some unwanted accounting costs.

Alhazmi et al. (2025) examined the impact of AI adoption on the quality of financial report on the Saudia stock exchange. The study explored how artificial intelligence (AI) impacted the quality of financial reporting, providing insights into new opportunities in this field for the Saudi context. The study employed the UTAUT theory to examine the adoption of AI technology in auditing practices. The study also utilized bibliometric analysis techniques through an academic literature review and content analyses of the documentary evidence. The implication of this study is that non-Big 4 audit firms should adopt AI-powered drones, which consequently enhance decision making, decrease audit fees, and enhance the quality of financial reports, and the efficiency and accuracy of audits. Furthermore, this paper recommends that non-Big 4 audit firms adopting AI should foster a culture of change to ensure quality audits and consistency, overcome resistance to the change, and support the integration of technologies such as AI-driven audit automation. The study also indicated the importance of integrating AI with the IFRS, developing a new framework for AI in auditing practices, incorporating AI into auditing courses, and modernizing auditing using AI. These implications lead to financial reports of enhanced quality. The results indicated four clusters, with artificial intelligence being the most significant keyword occurrence. This study has limitations, such as the lack of consideration of cyber-attack risks on drones, which may reduce the reliability of financial reports. Based on the findings of this research, audit companies and regulatory agencies in Saudi Arabia, like the Saudi Capital Market Authority (CMA), may evaluate the integration of AI to improve the quality of financial reporting. Implementing AI is expected to enhance the quality of audits, automate reporting, and support regulatory compliance to foster confidence and transparency in the financial industry.

Bin-Nashwan et al. (2025) examined how artificial intelligence adoption redefined financial reporting accuracy, auditing, efficiency and information asymmetry: An integrated model of TOE-TAM-RDT and big data governance. The study aimed to empirically explore what shapes AI adoption among AAFs, and what its potential role is in financial reporting accuracy, auditing efficiency, and information asymmetry. By applying a validated model of TOE-TAM-RDT and analysing using PLS-SEM, we found that AI adoption was shaped by competitive pressure, vendor ecosystem, top management support, relative advantage, AI readiness, and innovation climate. The adoption of AI-driven systems among AAFs exerted a positive impact on financial reporting accuracy, and auditing efficiency, while a negative impact on information asymmetry. Results further reveal a significant moderating effect of big data governance, demonstrating that proper management, quality, and ethical use of data within AAFs can amplify AI adoption benefits, boosting financial reporting accuracy, auditing efficiency, and mitigating information asymmetries between AAFs and stakeholders. These outcomes not only advance scholarly conversations on AI adoption in the financial and accounting landscape but also deliver actionable strategies for stakeholders to maximise AAFs' benefits from this emerging revolutionary technology.

Shi (2025) examined a literature review on the Application of artificial intelligence in financial statement analysis. The paper presents a comprehensive review of literature concerning the application of Artificial Intelligence in financial statement analysis, delineating the progress and current status of AI technologies in this domain. It explores the core of AI technologies and their practical applications. It further analyses the advantages and challenges associated with the integration of AI in financial statement analysis and offers insights into potential future research directions. The objective is to provide a valuable resource for advancing the in-depth applicatioin of AI in this field.

Oduwole and Fatogun (2023) critically examined the impact of artificial intelligence on accounting practice in the Nigerian banking industry. To attain the objectives of the study, a regression and correction model comprising independent variables (automation process, expert system, and intelligent agent) and dependent variables (accounting practice) was specified for the study. The data for this study were obtained from a primary source where a survey was carried out on banking industries in Nigeria; 133 respondents were chosen as the sample size, of which 128 were returned. The data were analyzed using regression method of inferential statistics to test the significance of hypotheses using the t-statistics of coefficient with the generated p-values. The findings revealed that all three variables (automation process, expect system, and intelligent agent) have a significant effect on accounting practice in deposit money banks (DMBs) industries in Nigeria. Therefore, the conclusion is that artificial intelligence enhances accounting practice in selected DMBs industries in Nigeria. It was recommended that banking industries and accountants, by improving their knowledge of artificial intelligence and enhancing their performance, will be able to eliminate some unwanted accounting costs.

Talea et al. (2025) investigated on advanced Artificial Intelligence and big data techniques in E finance: a comprehensive survey. The paper attempts a comprehensive review of literature through scholarly articles and papers published over the past thirteen years (2013–2025) available through Google Scholar and SCOPUS. The research methodology proceeded by choosing and crossing keywords related to technology and fintech, based on a bibliometric analysis of the past and current literature of related fields, the frequency of citation, and usage in emerging AI, Big Data, Text Mining, and Cloud computing trends in finance. Wide coverage was pursued by considering expert-reviewed high-ranking keywords drawn from the core areas of the field. The results identify the top publishers and journals holding significant influence in the field of E-finance. Moreover, this paper will also shed light on the possible benefits of text mining in finance which include improving customer satisfaction as well as detecting and preventing fraudulent transactions and risks mitigation. Results underscore the co-dependence between Finance, Technology, AI, Big Data, Text Mining, Cloud. And how they fit with each other; it further proposed a new methodology that detailed using multi-source datasets. However, these findings form valuable insights into the growing importance of emerging technologies upon the finance industry and current key trends in this area.

Abubakr et al. (2024) examined the Impact of AI Applications on Corporate Financial Reporting Quality: Evidence from UAE Corporations. The research aimed to identify the use of artificial intelligence applications as a pivotal technology to improve the quality of financial reports in UAE Corporations, as these applications help process and analyze data quickly and accurately. The problem of the study was the lack of confidence and credibility in the quality of financial reports in Corporations through some fictitious transactions that can affect the profits or losses of those Corporations. due to the effective role provided by artificial intelligence systems in the massive and rapid analysis of data, it was necessary to use these applications and employ them to enhance confidence in financial reports and achieve their quality, the study used Partial least squares (PLS) software in the analysis of the study came to the following conclusions: There is a statistically significant relationship between the use of artificial intelligence applications (AIA) and the quality of financial reporting (QFR) in UAE business Corporations, The study also came up with the following recommendations: The need to highlight the importance of artificial intelligence applications in business Corporations within the UAE, by developing the role of their applications in carrying out various routine and complex tasks and activities

Adeoye et al. (2023) examined the effect of artificial intelligence on audit quality by employing the survey method, using structured questionnaires administered to practicing accountants and staff of the Big Four accounting firms. The Taro Yamani formula was used to determine the sample size, and a total of 641 questionnaires were retrieved. Cronbach's alpha was employed to test the reliability and validity alongside the pilot testing conducted. Descriptive statistics and inferential analysis were also used. The results of the descriptive method showed that many of the respondents support the usefulness of artificial intelligence. The regression results revealed that artificial intelligence has a positive effect on audit quality. Based on the results, it is recommended that managers and accountants in private, corporate, and accounting firms should embrace the application of artificial intelligence due to its economic value and helpful effect of improving audit quality in terms of accuracy, reliability, and timely financial reporting.

Parker et al. (2023) examined whether the adoption of artificial intelligence (AI) in business operations improves financial reporting quality. They posit that AI technologies which automate data capture, extract complex data, and learn from experience to predict business parameters (e.g., demand, creditworthiness, defects, failures) can improve the quality of the estimates flowing into various reporting line items. Identifying US public firms that adopted AI (machine learning, robotics, etc.), from 2014-2018 with a proprietary dataset supplemented by public sources, They documented that AI adoption in business operations leads to greater financial reporting quality as reflected in lower discretionary accruals and closer mapping of accruals and cash flows. Instrumenting for AI adoption with the local availability of AI skills supports causal inference. AI adoption also improves the extent to which accounting estimates predict future cash flows, consistent with our hypothesized mechanism. We document spillover benefits for audit quality. As debates about the applications and risks of AI sweep the globe, our study offers archival evidence on its consequences in the realm of financial reporting.

Ndidiamaka and Chinedu (2025) investigated effect of artificial intelligence on predictive financial analysis in selected deposit money banks in Anambra State, Nigeria. The research modelled several independent variables, including the level of AI technology adoption, the use of machine learning algorithms, the volume of data processed by AI systems, the number of personnel trained in AI technologies, financial resources allocated for AI development, and the compatibility of AI systems with existing banking infrastructure. Utilizing a sample of 216 respondents, the study employs the Ordinary Least Squares (OLS) econometric regression technique to analyze the data. The regression results reveal that all independent variables have a significant positive impact on customer satisfaction. Specifically, the coefficient estimates indicate that for every unit increase in AI technology adoption, customer satisfaction increases by 0.32 ($p < 0.01$). The implementation of machine learning algorithms correlates with a 0.25 rise in customer satisfaction ($p < 0.05$), while an increase in the volume of data processed leads to a 0.30 ($p < 0.01$) improvement. The training of personnel contributes a 0.18 increase ($p < 0.05$), and financial resources dedicated to AI development show a significant coefficient of 0.22 ($p < 0.01$). Lastly, compatibility of AI systems has a coefficient of 0.27 ($p < 0.01$), indicating its critical role in improving services. The findings suggest that banks should prioritize the strategic adoption and integration of advanced AI technologies by assessing existing processes and fostering a culture of innovation. Investing in tailored machine learning solutions, robust data management infrastructure, and ongoing staff training will enhance personalized services and customer satisfaction. Additionally, ensuring compatibility of new AI systems with current infrastructure through careful planning and phased implementation will facilitate seamless integration and sustained service quality. The implications of this study are profound, highlighting the necessity for Nigerian banks to embrace AI not only as a technological upgrade but also as a driver for improved customer engagement and satisfaction. As the competitive landscape continues to evolve, those institutions that invest in AI-driven predictive analytics will likely secure a more stable and loyal customer base in the dynamic Nigerian financial market.

Oleimat et al. (2025) examined the impact of Artificial Intelligence on the quality of financial reports. The research examined the transformative role of the artificial intelligence in the financial reporting emphasizing its effects on accuracy, timeliness, transparency and regulatory compliance. Artificial Intelligence technologies such as Natural language processing, Machine learning and data analysis are revolutionizing traditional financial reporting processes by reducing manual effort, minimizing human errors and enhancing predictive applications. The study employed a mixed-method approach, it drew on interviews with industry professionals, academic literature reviews and industry reports. The findings revealed that Artificial intelligence significantly impact the accuracy and speed of financial reporting while fostering transparency and compliance. However challenges like algorithmic bias and data privacy concerns persist. They recommended that focusing on AI training, data governance and continuous monitoring to maximize the AI benefits while mitigating its risks.

Mohammed & Madloul (2025) examined the reflection of Artificial Intelligence technology on improving the quality of financial reports in commercial Banks; focusing on the impact of Artificial intelligence technologies on the quality of financial reporting by analyzing their role in enhancing the accuracy of financial data, reducing errors and promoting transparency in report preparation. The research problem centers on the lack of clarity; regarding the extent to which AI tools influences the quality of financial reports and their contribution to improving the accuracy and reliability of financial disclosure.

The study sample consists of ten commercial banking sector that provides services to individuals and businesses that adopt modern banking technologies. The sample included head of departments (accounting, auditing and credit) department managers, senior management personnel and other staff within the banks' organization structure. The researcher employed statistical analysis using questionnaires overall of which 103 were valid for the study. The results showed direct and statistically significant positive link between artificial intelligence technologies and financial report preparation. These findings confirm that using AI helps increase the degree of openness and raise the caliber of financial disclosure. Therefore, the researcher advises te broad use of these technologies in the banking industry as they help to improve the financial reporting system and support decision –making procedures; depending on correct dependable information.

Ogungbangbe & Alexanda (2024) investigated on Artificial intelligence and financial sector regulation: implication for accountants in Nigeria economy. The study examined how AI will affect accounting staff and how to prevent fraud. Since machines cannot make decisions, this technology won't result in widespread unemployment. Instead it will have a positive impact on the quality of accounting information. The study's conclusion highlights the need for staff to develop their seven area of expertise and become fully qualified personnel in the context of AI. According to the study's findings, auditors will be able to anticipate trends in the future and make better decisions that are aimed at enhancing audit procedures with the help of Artificial Intelligence. The study suggested increasing the use of image recognition to help with object classification, investing in machine learning tools in Nigeria Audit firms and providing accountants and audit staff with on-going training on data mining techniques to improve audit practice.

2.4 Summary of Empirical Review

Author and Year	Country	Objective	Methodology	Findings
Arefeh, 2024.	Iran (Tehran)	To examine the impact of accounting software on improving the accuracy and timeliness of financial reporting.	Descriptive Survey method with qualitative approach.	The results indicated that the use of accounting software has a positive and significant effect on the accuracy and timeliness of financial reports.
Pandey and Rana (2024)		To examine automatic financial report using accounting software based on artificial intelligence.	A cross-sectional survey with a standardized questionnaire.	According to the study's findings, accounting software efficiently gathers and analyses data and information to generate superior company reports.
Shah, (2025)	Nigeria	To explore the influence of artificial intelligence (AI) adoption on the timeliness of financial reporting among publicly listed firms.	Leveraging Multiple regression analysis.	The findings are expected to offer valuable insights into the relationship between digital transformation and reporting quality, with implications for regulators, investors, and corporate decision-makers aiming to strengthen corporate governance and stakeholder trust in the era of intelligent automation.
Al-Obaidy, (2024)	Iraq	To investigate on developing an accounting information system based on Artificial Intelligence to improve the quality of accounting information and the decision making process.	Utilized questionnaires.	The findings indicate that AI has a significant positive impact on both accuracy and efficiency of financial reporting.
Wilson-Oshilim and Efedhoma (2024)	Nigeria	To explore the impact of Artificial Intelligence (AI) on financial reporting accuracy and efficiency among Nigerian companies across various sectors.	Descriptive survey research design and quantitative analysis.	The findings indicate that AI has a significant positive impact on both accuracy and efficiency in financial reporting.
Shaban and Omoush (2025).	Jordan	To examine the impact of AI-driven financial transparency on corporate governance and regulatory reform.	Stratified random sampling approach	Contributed to the body of knowledge and providing insight for policy makers and corporate leaders.
Thanasa et al. (2025)		To examine the enhancing of transparency and efficiency in Auditing and regulatory compliance with		The paper suggested future directions such as wider blockchain adoption, AI-driven forcasting and the development of advanced cybersecurity measures.

		disruptive technologies.		
Aldemir and Uysal (2025)	Estonia, Singapore and Finland.	To examine Artificial Intelligence for financial accountability and governance in the public sector, strategic opportunities and challenges.	Qualitative case study.	The study reveals that AI-driven solutions such as predictive analytics, fraud detection systems and automated reporting significantly improves operational efficiency, transparency and decision making.
Unuesiri and Adejuwon (2024)	Nigeria	To investigate on the effect of Artificial Intelligence Expert System in the financial performance of Deposit Money Banks in Nigeria.	Non-probability convenience sampling.	The findings revealed that all the three variables have significant effect on accounting practice in deposit money banks.
Alhazmi et al. (2025)	Saudi Arabia	To examine the impact of AI adoption on the quality of financial report on the Saudia stock exchange.	Bibliometric analysis techniques.	The findings established that audit companies and regulatory agencies in Saudi Arabia may evaluate the integration of AI to improve the quality of financial reporting.
Bin-Nashwan et al. (2025)		To examine how AI adoption redefined financial reporting accuracy, auditing, efficiency and information asymmetry.	A validated model of TOE-TAM-RDT and analysing using PLS-SEM.	The adoption of AI-driven systems among AAFs exerted a positive impact on financial reporting accuracy, and auditing efficiency, while a negative impact on information asymmetry. Results further revealed a significant moderating effect of big data governance
Shi (2025)		To examine a literature review on the Application of artificial intelligence in financial statement analysis.	Bibliometric analysis of the past and current literature of related fields.	From the findings; it offers insights into potential future research directions.
Talea et al. (2025)		To investigate on advanced Artificial Intelligence and big data techniques in E finance: a comprehensive survey.	Bibliometric analysis of the past and current literature of related fields.	Results underscore the co-dependence between Finance, Technology, AI, Big Data, Text Mining, Cloud. And how they fit with each other; it further proposed a new methodology that detailed using multi-source datasets.
Abubakr et al. (2024)	United Arab Emirate (UAE)	To examine the Impact of AI Applications on Corporate Financial Reporting Quality: Evidence from UAE Corporations.	Partial least squares (PLS) software	There is a statistically significant relationship between the use of artificial intelligence applications (AIA) and the quality of financial reporting (QFR) in UAE business Corporations.
Adeoye et al. (2023)	Nigeria	To examine the effect of artificial intelligence	The survey method, using structured	The regression results revealed that artificial intelligence has a

		on audit quality.	questionnaires.	positive effect on audit quality.
Parker et al. (2023)	United states.	To examine whether the adoption of artificial intelligence (AI) in business operations improves financial reporting quality.	Discretionary accruals.	They documented that AI adoption in business operations leads to greater financial reporting quality as reflected in lower discretionary accruals and closer mapping of accruals and cash flows.
Ndidiamaka and Chinedu (2025)	Nigeria	To investigate the effect of artificial intelligence on predictive financial analysis in selected deposit money banks in Anambra State, Nigeria.	Ordinary Least Squares (OLS) econometric regression technique.	The findings suggest that banks should prioritize the strategic adoption and integration of advanced AI technologies by assessing existing processes and fostering a culture of innovation.
Mohammed and Madloul (2025)		To examine the reflection of Artificial Intelligence technology on improving the quality of financial reports in commercial Banks	Statistical analysis using questionnaires.	The results showed direct and statistically significant positive link between artificial intelligence technologies and financial report preparation.
Ogungbagbe and Alexanda (2024)	Nigeria	To investigate on Artificial intelligence and financial sector regulation: implication for accountants in Nigeria economy.	Review of previous literature.	The study suggested increasing the use of image recognition to help with object classification, investing in machine learning tools in Nigeria Audit firms and providing accountants and audit staff with on-going training on data mining techniques to improve audit practice.
Oleimat et al. (2025).		To examine the impact of Artificial Intelligence on the quality of financial reports.	The study employed a mixed-method approach.	The findings revealed that Artificial intelligence significantly impact the accuracy and speed of financial reporting while fostering transparency and compliance.
Oduwole and Fatogun (2023)	Nigeria	To examine the impact of Artificial Intelligence and accounting practice in Nigeria Banking Industry.	The data were analysed using regression method of inferential statistics to test the significance of hypotheses using the t-statistics of coefficient with the generated p-values.	The findings revealed that all three variables (automation process, expect system, and intelligent agent) have a significant effect on accounting practice in deposit money banks (DMBs) industries in Nigeria.

Author's compilation, 2025

2.5 Review of Theories

Agency Theory

Agency theory, developed by Jensen and Meckling (1976), focuses on the relationship between principals (e.g., shareholders) and agents (e.g., managers), where the latter may act in their own self-interest rather than in the best interest of the principals. In financial reporting, this theory explains the importance of transparency and accurate information flows between managers and shareholders to reduce information asymmetry and agency costs.

AI can play a crucial role in minimizing agency costs in financial reporting. By automating the preparation of financial statements and ensuring the accuracy of data inputs, AI reduces the potential for managerial manipulation or errors in reporting. This can help ensure that financial reports accurately reflect the company's true performance and reduce the conflict of interest between shareholders and management (Binns, 2018).

AI can also be seen as a mechanism that increases monitoring applications. Machine learning models, for example, can be used to detect anomalies in financial data that might indicate fraudulent activities or reporting discrepancies, thus enhancing the credibility of financial reports and reducing agency problems (Sundararajan, 2017).

Decision Theory

Decision theory is a broad framework that aims to explain how individuals or organizations make decisions under uncertainty. AI plays a significant role in financial reporting by improving decision-making through enhanced data analysis. Machine learning algorithms can analyze vast datasets to identify trends, correlations, and anomalies that might not be visible to human analysts. This enhanced decision-making process can help managers make more informed financial decisions and respond to market changes more effectively (Bessler & Biehl, 2017).

In the context of financial reporting, decision theory can be applied to understand how AI tools can aid in financial forecasting, budgeting, and risk management. By leveraging AI's ability to process complex financial data quickly and accurately, companies can make decisions based on more reliable and timely information, which in turn can improve the accuracy and relevance of their financial reports.

Stakeholder's Theory

Stakeholder theory explains that a company is responsible not only to its owners or shareholders but also to all other people or groups that are affected by its activities. These groups include employees, customers, suppliers, investors, the government, and the general public. According to Freeman (1984), stakeholders are any individuals or groups that can affect or be affected by the company's decisions. This means that a business should consider the interests of all these parties when making decisions, especially on how it reports its financial activities.

In relation to financial reporting, stakeholder theory suggests that companies should prepare and present financial information that is honest, clear, and useful to all stakeholders. Financial reports provide important information about a company's performance, financial position, and future prospects. When these reports are accurate and transparent, they help different stakeholders make informed decisions. For example, investors can decide whether to buy or sell shares, employees can assess job security, and regulators can check if the company is following accounting standards (Konstantin et al., 2017).

High-quality financial reporting builds trust between a company and its stakeholders. It shows that management is accountable and responsible. On the other hand, poor or misleading financial reporting can damage a company's reputation, lead to loss of investor confidence, and even result in legal problems. Therefore, stakeholder theory encourages organizations to be transparent and fair in their financial communication to protect the interests of all involved parties (Freeman et al., 2020). Stakeholder theory reminds companies that financial reporting is not just about meeting legal requirements or pleasing investors. It is about being open, honest, and responsible to everyone who depends on the company's information. By providing high-quality financial reports, companies can strengthen their relationships with stakeholders and ensure long-term success. The implementation of AI technologies enables organizations to generate more accurate and timely financial reports, thereby satisfying stakeholder information requirements. Through automation and intelligent data analysis, AI minimizes reporting errors and enhances transparency, which strengthens stakeholder confidence in the organization. Furthermore, Stakeholder Theory suggests that organizations should be accountable to all affected parties. AI-supported reporting systems improve accountability by providing comprehensive, real-time, and verifiable financial information. This aligns with the theory's central proposition that firms should create value through responsible stakeholder management rather than focusing exclusively on shareholder wealth maximization.

2.6 Gap in Literature

Despite the potential benefits of artificial intelligence on financial reporting such as enhancing, it's accuracy, reliability and efficiency; the actual impact of artificial intelligence applications on the quality of financial reporting in deposit money banks in Nigeria still remains an area of deficiency. There are limited studies from Nigeria and other developing countries that examined artificial intelligence application and financial reporting quality and their studies were not tailored towards artificial intelligence accounting, auditing, data analytics and predictive application in relation to financial reporting quality. This study would therefore explore the impact of Artificial Intelligence applications on financial reporting quality among deposit money banks in Nigeria using AI accounting, auditing, data analytics and predictive applications as proxy variables of artificial intelligence.

CHAPTER THREE

METHODOLOGY

3.1. Introduction

This chapter outlines the methods and procedures for conducting the study, including the research design, study population, sample size and sampling techniques, data sources, data collection methods, data analysis, model specification, and operationalisation of variables.

3.2. Research Design

Flowing from the statement of the research problems and the research questions, a quantitative research design was adopted for this study because it allowed for the systematic collection and analysis of numerical data to examine the relationship between artificial intelligence accounting, artificial intelligence data analytics, artificial intelligence auditing, artificial intelligence predictive applications and financial reporting quality objectively. This design is particularly suitable for studies that seek to measure the extent and frequency of an occurrence and to test hypotheses using statistical techniques. The quantitative approach enhances objectivity and minimises researcher bias as data are collected using structured instruments, such as questionnaires. This study examined the impact of artificial intelligence applications on financial reporting quality among deposit money banks in Nigeria.

3.3 Population of the Study

The population of this study comprised 2,839 accountants, auditors, and management staff of ten selected deposit money banks operating in Edo State, Nigeria. The selected banks were First Bank of Nigeria Plc, Zenith Bank Plc, Access Bank Plc, Fidelity Bank Plc, Guaranty Trust Bank Plc, Stanbic IBTC Bank Plc, First City Monument Bank (FCMB), Union Bank Plc, United Bank for Africa (UBA) Plc, and Keystone Bank Plc. The distribution of the population across the selected banks is presented in Table 3.1.

However, due to time and resource constraints, the study focused on the accountants, auditors, and management staff of the branches of the selected banks operating within the Benin City metropolis. Benin City was chosen because it hosts a substantial concentration of deposit money banks and provides adequate representation of banking operations within Edo State. Respondents were selected using stratified and purposive sampling techniques to ensure that relevant categories of staff with sufficient knowledge of accounting, auditing, management, and financial reporting practices were adequately represented in the study.

Table 3.1: Distribution of Study Population across Selected Deposit Money Banks

S/N	Bank	Accountants	Auditors	Management Staff	Total
1.	First Bank of Nigeria Plc	145	102	87	334
2.	Zenith Bank Plc	132	98	84	314
3.	Access Bank Plc	128	95	80	303
4.	Fidelity Bank Plc	120	90	75	285
5.	Guaranty Trust Bank Plc	125	92	78	295
6.	Stanbic IBTC Bank Plc	118	88	73	279
7.	First City Monument Bank (FCMB)	115	85	70	270
8.	Union Bank Plc	105	76	58	239
9.	United Bank for Africa (UBA) Plc	130	97	83	310
10.	Keystone Bank Plc	102	63	45	210
	Total	**1,220**	**886**	**733**	**2,839**

Source: HR Departments of Selected Deposit Money Banks (2025).

As presented in Table 3.1, the population of the study comprised 2,839 accountants, auditors, and management staff drawn from the ten (10) selected deposit money banks operating in Edo State, Nigeria. The distribution indicates that the population consisted of 1,220 accountants, 886 auditors, and 733 management staff. These categories of personnel were considered appropriate for the study because of their direct involvement in accounting operations, auditing activities, financial reporting processes, and managerial decision-making within the banking sector. The inclusion of respondents from different professional categories and banks was intended to ensure a broad representation of perspectives regarding the application of artificial intelligence in financial reporting. The next subsection explains the sample size determination.

3.4. Sample Size Determination and Sample Techniques

The sample size was derived from the Taro Yamane's formula propounded and postulated by Yamane (1967) for the determination of sample size in a finite population stated as:

$n = N/1+N(e)^2$

Where:

n = sample size

N = population size (finite population}

e = desired level of significance (5%)

$350.62 = 2839/1+2839\ (0.05)^2$

Rounding up to the nearest whole number the sample size would be approximately 351

n = 351

3.5. Type and Source of Data Collection

This study employed primary source of data collection. The primary source of data was elicited from the respondent as it concerns artificial intelligence applications and financial reporting quality among deposit money banks, in order to bring together raw information and first-hand evidence. The construction of questionnaire was necessary in meeting the said population who are expected to provide relevant information as regards their opinion on the study.

3.6 Research Instrument and Administration

The primary instrument used for data collection in this study was a structured questionnaire developed by the researcher. The questionnaire was neither adopted nor adapted from any previous study; rather, it was specifically designed based on the objectives of the study, the conceptual framework, and insights obtained from the reviewed literature on artificial intelligence applications and financial reporting quality. The questionnaire was considered appropriate because it enabled the collection of firsthand information from accountants, auditors, and management staff of selected deposit money banks. The questionnaire was administered electronically through Google Forms to facilitate wider coverage, ease of distribution, and prompt retrieval of responses.

The questionnaire was divided into six sections. Section I elicited information on the demographic characteristics of the respondents, including age, sex, educational qualification, bank affiliation, and religion. Section A measured financial reporting quality using five questionnaire items relating to relevance, faithful representation, comparability, reliability, and timeliness of financial reports. Section B measured the artificial intelligence accounting application using five items designed to assess the extent to which artificial intelligence supports accounting processes and reporting activities within the banks. Section C measured artificial intelligence data analytics and assessed it using five items that evaluated how artificial intelligence is applied when analysing financial data and enhancing reporting quality. Section D measured artificial intelligence auditing and consists of five items that focus on the use of artificial intelligence in auditing activities, transaction verification, and assurance processes. Section E measured artificial intelligence predictive application using five items that assessed the extent to which predictive artificial intelligence applications contribute to improved financial reporting quality.

All measurement items were structured on a five-point Likert scale of Strongly Agree (5), Agree (4), Undecided (3), Disagree (2), and Strongly Disagree (1). The responses obtained from the questionnaire formed the basis for the statistical analyses conducted in the study.

3.7 Validity of the Instrument

The questionnaire used for this study was subjected to face-to-face and content validity assessments to ensure that the items adequately measured the constructs under investigation. Since the instrument was developed by the researcher, copies of the questionnaire were submitted to the supervisor and other experts with knowledge in accounting, financial reporting, research methodology, and artificial intelligence for review. Their observations, suggestions, and corrections were incorporated into the final version of the questionnaire to enhance clarity, relevance, and adequacy of the measurement items. The validation process ensured that the instrument was appropriate for achieving the objectives of the study and addressing the research questions.

3.8. Analytical Framework and Theoretical Framework

This analytical framework in Fig. 3.1 below depicts a schematic representation of the causal relationships between the dependent variable (financial reporting quality) and the independent variable (artificial intelligence applications, i.e., artificial intelligence accounting, data analytics auditing, and predictive applications) for the purpose of this study.

This study was anchored on the agency, decision and stakeholder theories. Agency theory, which was developed by Jensen and Meckling (1976), focuses on the relationship between principals (e.g., shareholders) and agents (e.g., managers), where the latter may act in their self-interest rather than in the best interest of the principals. In financial reporting, this theory explains the importance of transparency and accurate information flows between managers and shareholders to reduce information asymmetry and agency costs. AI can play a crucial role in reducing agency costs in financial reporting. By automating the preparation of financial statements and ensuring the accuracy of data inputs, AI reduces the potential for managerial manipulation or errors in reporting. This can help ensure that financial reports accurately reflect the company's true performance and reduce the conflict of interest between shareholders and management (Binns, 2018).

This study also used decision theory to examine artificial intelligence and financial reporting quality. On the other hand, decision theory is a broad framework that aims to explain how individuals or organisations make decisions under uncertainty. Furthermore, the stakeholder's theory was also used to examine artificial intelligence and financial reporting quality. Stakeholder theory states that a company is accountable to all those affected by its actions, not just its owners or shareholders. These groups include employees, customers, suppliers, investors, the government, and the general public. According to Freeman (1984), stakeholders are any individuals or groups that can influence or be affected by the company's decisions.

Artificial intelligence plays a significant role in financial reporting quality by improving decision-making through enhanced data analysis. Machine learning algorithms can analyse vast datasets to identify trends, correlations, and anomalies that might be invisible to human analysts. This enhanced decision-making process can help managers make more informed financial decisions and respond to market changes more effectively (Bessler & Biehl, 2017). The study therefore aimed to explore the extent to which the application of artificial intelligence to accounting, data analytics, auditing and predictive analytics impacts financial reporting quality in deposit money banks (financial institutions) in Nigeria.

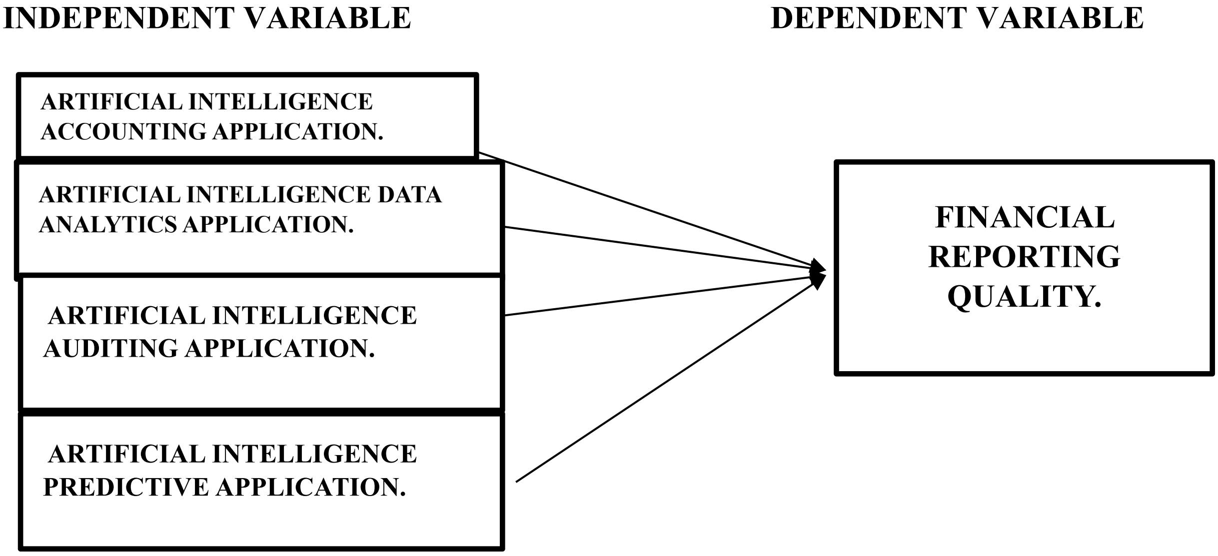

Fig 3.1: Schematic Model of the Determinants of AI and FRQ

Source: ***Author's Analytical Framework (2025)***

3.9 Model Specification

The model for this study was adapted from Unuesiri and Adejuwon (2024), who examined the effect of Artificial Intelligence Expert System on the financial performance of deposit money banks in Nigeria. The authors specified their functional model as:

$Perf = (ES)$ −−−−−−−−−−−−−−−−−−−−− (1)

The econometric form of their model was expressed as:

$Perf = \beta 0 + \beta 1 LOGES + DY + \mu$ −−−−−−−−−−−−−−−−−− (2)

Where:

Perf = Bank Performance

LOGES = Natural Logarithm of Artificial Intelligence Expert System

DY = Dummy Variable capturing pre- and post-AI adoption periods

β_0 = Intercept

β_1 = Coefficient of the explanatory variable

μ = Error term

However, going by analytical framework of this study (see Figure 3.1), this study modified above the model to suit its objectives and research design. Specifically, the study replaced bank performance with financial reporting quality as the dependent variable. In addition, the single Artificial Intelligence Expert System variable used in the original model was disaggregated into four dimensions, namely Artificial Intelligence Accounting Application, Artificial Intelligence Data Analytics Application, Artificial Intelligence Auditing Application, and Artificial Intelligence Predictive Application. The dummy variable included in the original model was excluded because the present study employed a cross-sectional survey design rather than a pre- and post-adoption time-series approach.

Consequently, the functional model for the present study is specified as:

$$\mathrm{FRQ} = \mathrm{f}(\mathrm{AIACAP}, \mathrm{AIDAAP}, \mathrm{AIADAP}, \mathrm{AIPAP}) - - - - - - - - - - - - - - - - - - \quad (3)$$

The econometric form of the model is expressed as:

$$\mathrm{FRQ} = \beta_0 + \beta_1\mathrm{AIACAP} + \beta_2\mathrm{AIDAAP} + \beta_3\mathrm{AIADAP} + \beta_4\mathrm{AIPAP} + \mu - - - - - - - \quad (4)$$

Where:

FRQ = Financial Reporting Quality

AIACAP = Artificial Intelligence Accounting Application

AIDAAP = Artificial Intelligence Data Analytics Application

AIADAP = Artificial Intelligence Auditing Application

AIPAP = Artificial Intelligence Predictive Application

β_0 = Intercept of the model

$\beta_1 - \beta_4$ = Coefficients of the explanatory variables

μ = Stochastic error term

The a priori expectations of the study are:

$$\beta_1 > 0, \beta_2 > 0, \beta_3 > 0, \beta_4 > 0$$

This implies that improvements in Artificial Intelligence Accounting Application, Artificial Intelligence Data Analytics Application, Artificial Intelligence Auditing Application, and Artificial Intelligence Predictive Application are expected to positively influence Financial Reporting Quality.

3.10 Operationalisation of Variables

Variables	Type	Measurement	A-priori Expectation	Source
Financial Reporting Quality.	Dependent	IASB fundamental and enhancing qualitative index such as relevance, faithful representation, understandability, comparability, verifiability and timeliness.	Nil	Mbobo & Umoren 2016; Osasere & Ilaboya 2018.
Artificial Intelligence Accounting Application.	Independent	Efficiency, Accuracy and Fraud detection (machine learning)	Positive	Khorseed et al (2024).
Artificial Intelligence Data Analytic Application.	Independent	Knowledge base, Inference engine, Explanation component. Operational efficiency and decision quality (expert system)	Positive	Alttar et al (2024), Unuesiri & Adejuwon (2024).
Artificial Intelligence Auditing Application.	Independent	Sentiment analysis: text extraction (tokenization, stop word removal) and Feature extraction (bag of word, Term Frequency- Inverse Document Frequency (natural language processing)	Positive or negative	Sarode & Singh (2024).
Artificial Intelligence Predictive Application.	Independent	Efficiency, Accuracy and Fraud detection (machine learning)	Positive	Khorseed et al (2024).

Source: Author's compilation (2025)

3.11 Method of Data Analysis

The study utilised both descriptive and inferential statistics for data analysis. The descriptive statistics includes respondents' perception, mean and standard deviation while the inferential statistics involved Pearson correlations, variance inflation factor and least squares regression analysis. Data generated through questionnaire were estimated using Statistical Packages for Social Science also known as Statistical Package for Service and Solutions (SPSS) version 21.

CHAPTER FOUR

DATA PRESENTATION AND ANALYSIS

4.1 Introduction

This chapter was concerned with outcomes of questionnaire copies successfully retrieved from respondents who were staff of deposit money banks. Results were analysed to obtain answers to our research questions and specific objectives. Successfully retrieved copies of questionnaire were estimated with computer software (Statistical Packages for Social Sciences otherwise known as Statistical Package for Service and Solutions (SPSS version 21). These were analysed and interpreted in headings and sub-headings which included data presentation and interpretations of results, correlation matrix, least squares regression method, test of hypotheses and discussion of findings.

4.2 Data Presentation and Interpretation

This section actually examined copies of questionnaire administered and successfully retrieved as illustrated in Table 4.1.

Table 4.1: Questionnaire Distribution and Response Rate

Description	Number
Projected sample size distributed through Google Forms	351
Questionnaires returned	349
Questionnaires rejected due to incomplete responses	2
Usable questionnaires	347
Response rate (%)	**98.86**

Source: Researcher's Feld Work (2025)

As presented in Table 4.1, a total of 351 questionnaires were administered to accountants, auditors, and management staff of the selected deposit money banks through Google Forms. Out of the 351 questionnaires distributed, 349 were successfully returned, representing a return rate of 99.43%. However, 2 of the returned questionnaires were excluded from the analysis due to incomplete responses. Consequently, 347 questionnaires were found usable and were utilised for the study, representing an effective response rate of 98.86%. The high response rate indicates a strong level of participation by the respondents and provides sufficient data for the subsequent analyses presented in this chapter.

4.3 Characteristics of Sample Respondents

This sub-section is concerned with profile of respondents. Issues examined in this section include demographic profile of the respondents, analysis and interpretation of respondents' perceptions as highlighted in the Tables 4.1 below:

Table 4.2: Demographic Characteristics of Respondents

Demographic Characteristic	Options	No	Percentage %
Gender	Male	191	55.0
	Female	156	45.0
	TOTAL	347	100.0
Marital Status	Single	91	26.2
	Married	256	73.8
	TOTAL	**347**	**100.0**
Age	18-30	165	47.6
	31-40	126	36.3
	41-50	39	11.2
	51-65	17	4.9
	TOTAL	**347**	**100.0**
Educational qualification attained	Diploma/NCE	79	22.8
	HND/ B.Sc.	66	19.0
	MBA/ M.Sc.	171	49.3
	Ph.D.	25	7.2
	Professional Certificates	6	1.4
	TOTAL	**347**	**100.0**
Working experience	1-10	245	70.6
	11-20	52	15.0
	21-30	35	10.4
	31 -40	14	4.0
	41 and above	1	0.3
	TOTAL	**347**	**100.0**

Source: Author's Field work (2025)

Table 4.2 highlights profile or demographic characteristics of the constituted respondents. It is observed that out of 347 gender of respondents, 191 respondents representing 55% were male, while 156 respondents representing 45% were female staff of banks. Also, from the total marital status of respondents, 91 respondents representing 26.2% were single, while 256 representing 73.8% respondents were married men and women management staff of banks.

As regards the ages of respondents, a total of 165 representing 47.6% were within the ages of 18-30 years, 126 respondents representing 36.3% were within 31-40 years of age, 39 respondents representing 11.2% were within ages of 41-50 years, while 17 respondents representing 4.9% are within the ages of 51-60 years.

Going by educational qualifications of respondents, it was observed that a total of 79 respondents representing 22.8% staff possess Diploma Certificate and National Certificate of Education, 66 respondents representing 19.0% possess Higher National diploma and bachelor degrees; 171 respondents representing 49.3% possess masters degrees, 25 respondents representing 7.2% possess PhD qualifications, while 6 respondents .representing 1.7% possess professional certificates.

In case of working experience, 245 respondents representing 70.6% have worked in the banking sector for 1-10 years, 52 respondents representing 15% have worked for 11-20 years, 35 respondents representing 10.4% have worked for 21-30 years, 14 respondents representing 4% have worked for 31-40 years, while only 1 respondent representing 0.3% had worked for over 40 years.

4.4 Descriptive Statistics

This section examines respondents' perception based on research questions and objectives of study as below:

Table 4.3: Respondents Perceptions on Financial Reporting Quality

	Statement question	N	Responses					Descriptive Statistics	
			Strongly Agreed	Agreed %	Neutral %	Disagreed %	Strongly Disagreed	Mean	Standard Deviation
1	Quality financial report facilitates relevance by the stakeholders	347	*253 (72.9)*	*93 (26.8)*		*1 (0.3)*		4.72	0.467
2	Quality financial report promotes faithful representation of report by the interest of users.	347	*267 (76.9)*	*76 (21.9)*	*1 (0.3)*	*2 (0.6)*	*1 (0.3)*	4.75	0.515
3	Quality financial report facilitates comparability of the report by the stakeholders.	347	*187 (53.9)*	*156 (45.0)*	*4 (1.2)*			4.53	0.523
4	Quality financial report can promotes reliability of report by the stakeholders.	347	*201 (57.9)*	*139 (40.1)*	*7 (2.0)*			4.56	0.536
5	Quality financial report facilitates timeliness in informed decision making by users.	347	*198 (57.1)*	*143 (41.2)*	*5 (1.4)*		1 (0.3)	4.55	0.559
								4.622	0.52

Source: ***Researcher's Field work (2025)   Highly considered assumed mean=3.0***

Table 4.3 shows respondents' perceptions on issues relating to financial reporting quality. It was observed that a total of 346 (99.7%) respondents agreed that quality financial report facilitates relevance by the stakeholders, while 1(0.3%) respondent disagreed. The computed mean value of 4.75 was higher than the bench value of 3.0 and standard deviation of 0.515 which further suggests that most of the respondents were of agreed perceptions

It was also deduced that a total of 343 (98.8%) respondents were of the agreed opinion that quality financial report promotes faithful representation of report by the interest of users, 1 (0.3%) respondents were of neutral opinion to the statement, while 3(0.9%) respondents were of the disagreed view. Outcome of the calculated mean value of 4.75 was greater than standard deviation of 0.515 and bench mark mean value of 3.0, which further indicated that most of the respondents were of the agreed opinion.

Similarly, a total of 343 (98.8%) respondents were of agreed perception to the statement question that quality financial report facilitates comparability of the report by the stakeholders, while 4 (1.2%) respondents were neutral in perception. The results of respondents calculated mean of 4.53 is higher than the bench mark mean value of 3.0 and standard deviation of 0.525, suggesting that most of the respondents were of agreed perceptions to the statement question.

Furthermore, a total of 340 (98%) respondents were of the agreed view that quality financial report can promote reliability of report by the stakeholders, while 7(2.0%) respondents were neutral. The outcome of respondents perceptions coupled with the calculated mean value of 4.56 which is higher than the bench mark value of 3.0 and standard deviation of 0.536 implied that greater proportion of respondents were of the agreed perceptions.

It was also noted that a total of 341(98.2%) respondents were of the agreed view that Quality financial report facilitates timeliness in informed decision making by users, 5(1.5%) respondents were of neutral perception, while 1(0.3%) of the respondents disagreed to this view. The high calculated mean value of 4.55 compared to low standard deviation of 0.536 and assumed mean value of 3..0, indicated that most respondents were of the agreed opinion.

The overall calculated mean value of 4.622 which is greater than standard deviation of 0.52 and assumed mean value of 3.0 suggested that majority of the respondents were of the agreed opinion on questions relating to financial reporting quality.

Table 4.4: Artificial Intelligence Accounting application and Financial Reporting Quality

S/N	Statement Question	N	Respondents					Descriptive Statistics	
			Strongly Agreed(%)	Agreed(%)	Neutral(%)	Disagreed(%)	Strongly Disagreed(%)	Mean	Standard Deviation
6	Artificial Intelligence can help generate relevant and reliable data for preparation of accounts in my bank	347	220 (63.4)	116 (33.4)	6 (1.7)	3 (0.9)	2 (0.6)	4.58	0.632
7.	Artificial Intelligence can assist in generating information and evidences for preparation of accounts without delay in my bank	347	188 (54.2)	131 (37.8)	23 (6.6)	5 (1.4)		4.45	0.684
8.	Artificial Intelligence can help in timely posting of financial transactions that can be relied on by stakeholders of my bank	347	190 (54.8)	150 (43.2)	6 (1.7)	1 (0.3)		4.52	0.550
9.	Artificial Intelligence can facilitate reconciliation of financial statements that can be reliable by stakeholders of my bank	347	184 (53.0)	156 (45.0)	4 (1.2)	2 (0.6)	1 (0.3)	4.50	0.586
10.	Artificial Intelligence can assist in balancing of transactions timely without errors in my bank	347	179 (51.5)	162 (46.7)	5 (1.5)		1 (0.3)	4.49	0.561
	Overall mean index							**4.508**	**0.603**

Source: ***Researcher's Field work (2025)*** ***Highly considered assumed mean=3.0***

Table 4.4 shows Artificial Intelligence Accounting application and Financial Reporting Quality. A total of 336(96.8%) respondents were of agreed opinion that Artificial Intelligence can help generate relevant and reliable data for preparation of accounts in my bank 6(1.8%) respondents were neutral, and 5 (1.5%) respondents disagreed to the statement question. The calculated mean value of 4.58 was greater than standard deviation of 0.632 and assumed mean value of 3.0 implying that most of the respondents were of the agreed opinion.

It was observed that 319(92%) respondents were of the agreed perceptions that Artificial Intelligence can assist in generating information and evidences for preparation of accounts without delay in my bank 23 (6.6%) respondents were neutral, while 5 (1.5%) respondents were of the disagreed perception. The mean value of 4.45 was greater than assumed mean value of 3.0 meaning that most of the respondents were of the agreed opinion.

Also, a total of 340(98%) respondents were of the agreed opinion that bank Artificial Intelligence can help in timely posting of financial transactions that can be relied on by stakeholders of my bank 6(1.8%) respondents were of neutral opinion, while 1(0.3%) respondents was of the disagreed opinion. The calculated mean value of 4.52 is greater than mean bench mark of 3.0 and standard deviation of 0.550 indicating that majority of respondents were of the agreed views.

In the same vein, a total of 340(%) respondents were of the agreed view that Artificial Intelligence can facilitate reconciliation of financial statements that can be reliable by stakeholders of my bank 4(1.2%) were neutral, while 3(0.9%) respondents were of the disagreed perceptions. The computed mean value of 4.50 compared to low standard deviation and assumed mean value of 0.586 and 3.0 respectively suggesting that most of the respondents were of the agreed view to the statement.

Also, total of 341 (98.3%) respondents were of the agreed perception that Artificial Intelligence can assist in balancing of transactions timely without errors in my bank 5 (1.5%) respondents were neutral, while 1(0.3%) respondents were of the disagreed view. The mean outcome of 4.49 is greater than standard deviation of 0.561 and bench mean of 3.0 implying that greater proportion of the respondents were of the agreed perceptions.

The overall computed mean index of 4.508 compare to standard deviation of 0.603 and assumed mean value of 3.0, implied that most of the respondents were of the agreed perceptions on statement questions relating to artificial intelligence accounting application and financial reporting quality.

Table 4.5: Respondents Perception on Artificial Intelligence Data Analytics application and Financial Reporting Quality

Statement Questions		N	Respondents					Descriptive Statistics	
			Strongly Agreed (%)	Agreed(%)	Neutral(%)	Disagreed(%)	Strongly Disagreed(%)	Mean	Standard Deviation
11	Artificial intelligence application in analysing past financial data can foster quality report in my bank.	347	201 (57.9)	141 (40.6)	2 (0.6)	2 (0.6)	1 (0.3)	4.55	0.573
12	Artificial intelligence application in describing financial data estimated can help to evaluate quality report in my bank.	347	247 (71.2)	96 (27.7)	2 (0.6)	1 (0.3)	1 (0.3)	4.69	0.527
13	Artificial intelligence	347	198	145	2	1	1	4.55	0.558

	application in analysing present financial data can help to improve quality financial report in my bank.		(57.1)	(41.8)	(0.6)	(0.3)	(0.3)		
14	Use of artificial intelligence in analysing transactions data patterns can assist to make informed decision that can enhance quality financial report in my bank	347	204 (58.8)	136 (39.2)	5 (1.4)	1 (0.3)		4.57	0.541
15	Artificial intelligence application in analyzing various books of accounts prepared can enhance quality financial report in my bank	347	222 (64.0)	113 (32.6)	10 (2.9)	2 (0.6)		4.60	0.577
	Overall mean index							4.592	0. 555

Source: ***Researcher's Field work (2025)   Highly considered assumed mean=3.0***

Table 4.5 examines respondents' perception on questions relating to artificial intelligence data analytics application and financial reporting quality It showed that a total of 342(98.5%) respondents were of the agreed opinion that artificial intelligence application in analysing past financial data can foster quality report in my bank, 2(0.6%) respondents were neutral, while 3(0.9%) of the respondents disagreed to this view. The calculated mean value of 4.06 was above standard deviation of 0.573 and bench mean of 3.0 indicating that most respondents were of the agreed opinion.

Also, a total of 343(98.8%) respondent were of the agreed perceptions that artificial intelligence application in describing financial data estimated can help to evaluate quality report in their banks. 2(0.6%) respondents were neutral, while 2(0.6%) respondents were of the disagreed opinion. The computed mean value of 4.69 is higher than standard deviation and assumed mean value of 0.527 and 3.0 respectively indicating that greater proportion of the respondents were of the agreed perceptions.

It was also deduced that a total of 343(98.8%) respondents were of the agreed assertion that artificial intelligence application in analysing present financial data can help to improve quality financial report in their banks..2(0.6%) respondents were neutral, while a total of 2(0.6%) respondent were of the disagreed perceptions. The computed mean value of 4.55 was higher than standard deviation of 0.588 and bench mean value of 3.0 respectively indicating that most respondents were of the agreed perceptions.

Furthermore, a total of 340(98%) respondents were of the agreed opinion that the use of artificial intelligence in analysing transactions data patterns can assist to make informed decision that can enhance quality financial report in their banks 15(4.8%) respondents were neutral, 19(6.2%) of the respondents disagreed to this view. The calculated high mean value of 4.57 implied that most of the respondents were of the agreed perceptions

It was also pointed out that 335(96.6%) respondents were of the agreed perception that Artificial intelligence application in analyzing various books of accounts prepared can enhance quality financial report in my bank 10 (2.9%) respondents were neutral, while the remaining 2(0.6%) of the respondents disagreed to this view. The computed mean value of

4.60 was higher than standard deviation of 0.577 and bench mean value of 3.0 respectively indicating that most respondents were of the agreed perceptions.

The high overall mean value of 4.592 indicated that most of the respondents were of the agreed perception that relating to artificial intelligence data analytics application and financial reporting quality

Table 4.6: Artificial Intelligence Auditing application and Financial Reporting Quality

Statement Questions		N	Respondents					Descriptive Statistics	
			Strongly Agreed (%)	Agreed (%)	Neutral (%)	Disagreed(%)	Strongly Disagreed(%)	Mean	Standard Deviation
16	Use of Artificial Intelligence in examining accuracy of financial transactions data can help in facilitating quality financial report in my bank.	347	203 (58.5)	136 (39.2)	5 (1.4)	2 (0.6)	1 (0.3)	4.55	0.589
17	Use of Artificial Intelligence in auditing evidences of financial transactions can help in ensuring quality financial report in my bank	347	213 (61.4)	128 (36.9)	5 (1.4)		1 (0.3)	4.59	0.553
18	Use of Artificial Intelligence in auditing entries and posting of financial transaction can foster quality financial report in my bank.	347	211 (60.8)	131 (37.8)	4 (1.2)		1 (0.3)	4.59	0.548
19	Use of Artificial	347	183	159	2	2	1	4.50	0.576

	Intelligence in auditing promotes timeliness in financial report in my bank		(52.7)	(45.8)	(0.6)	(0.6)	(0.3)		
20	Artificial intelligence auditing application of various books of accounts can foster quality financial report for the interest of stakeholders of my bank.	347	204 (58.8)	106 (30.5)	28 (8.1)	4 (1.2)	5 (1.4)	4.44	0.807
	Overall Mean index							4.53	0.615

Source: ***Researcher's Field work (2025)   Highly considered assumed mean=3.0***

Table 4.6 highlights respondents' views on questions relating to artificial intelligence auditing application and financial reporting quality. It was established that a total of 339(97.7%) respondents were of the agreed opinion that use of artificial intelligence in examining accuracy of financial transactions data can help in facilitating quality financial report in my bank, 5(1.4%) respondents were neutral, while 3(0.9%) respondents were of the disagreed perception. The high mean value of 4.56 compared to low standard deviations implied that most of the respondents were of the agreed opinion to the statement question.

It was observed that a total of 341(98.3%) respondents were of the agreed assertion that Use of Artificial Intelligence in auditing evidences of financial transactions can help in ensuring quality financial report in my bank 5(1.4%) respondents were neutral, while 1(0.3%) respondents were of the disagreed opinion. The computed mean value of 4.59 compare to assumed mean of 3.0 showed that most of the respondents were on the agreed.

Also, a total of 342(98.6%) respondents were of the agreed view that Use of Artificial Intelligence in auditing entries and posting of financial transaction can foster quality financial report in my bank. 4(1.2%) respondents were neutral, while 1(0.3%) respondents were of the disagreed. The mean value of 4.59 compared to the standard deviation 0.576 and bench mean mark of 3.0, implied that most of the respondents were of the agreed perception

It was also noted that a total of 342(98.5%) respondents were of the agreed view that Use of Artificial Intelligence in auditing promotes timeliness in financial report in my bank 2(0.6%) respondents were of neutral opinion, while 3(0.9%) of the respondents disagreed. The high calculated mean of 4.60 was further indication that most of the respondents were in support of the agreed perceptions.

In addition, a total of 310(98.5%) respondents were of the agreed view that Artificial intelligence auditing application of various books of accounts can foster quality financial report for the interest of stakeholders of my bank. 28(8.1%) respondents were neutral, while 9(2.4%) respondents were of the disagreed view. Its computed mean value is 4.44 while assumed mean indicated 3,0 suggesting that most of the respondents were of the agreed opinion.

However, the overall computed mean value of 4.534 as against low standard deviation and bench mark mean value of 0.6146 and 3.0 respectively basically implied that most of the respondents were of the agreed assertions that most of the respondents were of the agreed opinion on issues relating to artificial intelligence data analytics application and financial reporting quality

Table 4.7: Artificial Intelligence Predictive application and Financial Reporting Quality

	Statement Questions	**N**	**Respondents**					**Descriptive Statistics**	
			Strongly Agreed(%)	**Agreed(%)**	**Neutral(%)**	**Disagreed(%)**	**Strongly Disagreed(%)**	**Mean**	**Standard Deviation**
21	Artificial Intelligence predictive application can foster relevance of financial report for the interest of stakeholderss of my bank	347	183 (52.7)	142 (40.9)	14 (4.0)	5 (1.4)	3 (0.9)	4.43	0.720
22	Artificial Intelligence	347	146	110	12	45	34	3.83	1.354

	predictive application can facilitate faithful representation of financial report for the interest of stakeholders of my bank		(42.1)	(31.7)	(3.5)	(13.0)	(9.8)		
23	Artificial Intelligence predictive application can promote comparability of financial report for the interest of stakeholders of my bank	347	223 (64.3)	106 (38.5)	9 (2.6)	7 (2.0)	2 (0.6)	4.56	0.700
24	Artificial intelligence predictive applications can help to detect irregularities and promote quality financial report of my bank	347	246 (70.9)	88 (25.4)	11 (3.2)	2 (0.6)		4.67	0.567
25	Artificial intelligence predictive application can facilitate quality of financial report of my bank	347	209 (60.2)	113 (32.6)	8 (2.3)	12 (3.5)	5 (1.4)	4.47	0.823
	Overall Mean Index							4.39	0.833

Source: ***Researcher's Field work (2025)   Highly considered assumed mean=3.0***

Table 4.7 presents respondents' views on statements regarding the predictive applications of artificial intelligence (AI) in relation financial reporting quality of bank. The findings reveal that 325 respondents (93.6%) agreed that Artificial Intelligence predictive application can foster relevance of financial report for the interest of stakeholders of my bank while 14 respondents (4.0%) were neutral, and 8 respondents (2.3%) disagreed. The high mean value of 4.43 suggests that most respondents supported this view.

Additionally, 256 respondents (73.8%) agreed that artificial intelligence predictive application can facilitate faithful representation of financial report for the interest of stakeholders of my bank while 12 respondents (3.5%) were neutral, and 79 respondents (22.8%) disagreed. The mean value of 3.83 and a low standard deviation of 1.354, compared to the assumed mean of 3.0, further indicate that the majority agreed with this statement.

Similarly, 329 respondents (94.8%) agreed that artificial intelligence predictive application can promote comparability of financial report for the interest of stakeholders of my bank while 9 respondents (2.6%) were neutral, and another 9 (2.6%) disagreed. The high mean value of 4.56 and a low standard deviation of 0.700 compared to the assumed mean of 3.0 reaffirm that most respondents shared this perception.

Moreover, 334 respondents (96.3%) agreed that artificial intelligence predictive application can help to detect irregularities and promote quality financial report of my bank,11 respondents (3.2%) were neutral, and 2 respondents (0.6%) disagreed. The high mean value of 4.67 and a low standard deviation of 0.567, relative to the assumed mean of 3.0, indicate strong agreement among respondents.

Furthermore, 322 respondents (93.6%) agreed that artificial intelligence predictive application can foster quality of financial report of my bank, whereas 8 respondents (2.3%) were neutral, and 17 respondents (4.9%) disagreed. The mean value of 4.47 and a standard deviation of 0.823, compared with the assumed mean of 3.0, suggest that the majority supported this viewpoint.

Overall, the mean index value of 4.392, which is higher than the standard deviation (0.8328) and the benchmark assumed mean value of 3.0, indicates that greater proportion of respondents were of the agreed opinion on questions relating to artificial intelligence predictive application in relation to financial reporting quality of bank.

4.5 Diagnostic Tests

The various diagnostic tests carried out in this study include Pearson correlations; Kaiser Meyer-Olkin (KMO) and Barlett's Tests which were analysed as follows:

Table 4.8:Pearson Correlations

	FRQ	AIACAP	AIDAAP	AIADAP	AIPAP
FRQ	1	.			
AIACAP	.014	1			
AIDAAP	.058	.049	1		
AIADAP	.102	-.010	.158**	1	
AIPAP	.037	.153**	.084	-.027	1

**. and *Correlations are significant at 0.01 and 0.05level (1-tailed and 2-tailed).

Researcher's Compilation (2025) (SPSS21)

Table 4.8 presents the associations among variables and examines the presence of multicollinearity in the data collected through the questionnaire. The findings indicate that when financial reporting quality (FRQ=1) was at its perfect unit value, artificial intelligence accounting application (AIACAP was at a correlation value of 0.014 (1%), artificial intelligence data analytic application (AIDAAP was at 0.058 (6%), artificial intelligence auditing application (AIADAP) was at correlation value of 0.102 (10%), and artificial intelligence predictive application (AIPAP) stood at 0.037(4%). The Pearson correlation matrix showed positive associations between artificial intelligence proxied variables and financial reporting quality at 0.01significance levels (2-tailed tests). Since none of the variables exhibited a perfect correlation or exceeded the 0.80 (80%) threshold, as recommended by Hair et al. (2020) for detecting multicollinearity, it was concluded that multicollinearity was not present in the dataset. These results confirm that the data were suitable for regression analysis. Thus, proceed to variance inflation factor (VIF) test to further check the strength of the dataset, as presented in Table 4.9

Table 4.9: Variance Inflation Factor

Variables	**VIF Collinearity Test**
AIACAP	1.059
AIDAAP	1.024
AIADAP	1.009
AIPAP	1.058

Source: Researcher's Computation (2025) (SPSS 21) (See Appendix IV for detailed result)

Table 4.9 shows the results of the variance inflation factor (VIF) diagnostic test to further check the strength of the Pearson correlation if there exists potential multicollinearity in the data used for the purpose of ordinary least squares regression. The VIF threshold for the absence of multicollinearity is set at 10 units, while any value exceeding this threshold indicates the presence of multicollinearity (Hair, Black, Babin & Anderson, 2010).

The results revealed that the VIF values were relatively low, with artificial intelligence accounting application (AIACAP) at 1.059, artificial intelligence data analytics application (AIDAAP) at 1.024, artificial intelligence auditing application (AIADAP) at 1.009, and artificial intelligence predictive application (AIPAP) at 1.056. These results reinforce the correlation matrix results, confirming that multicollinearity will not an issue in the regression analysis, as none of the variables exceeded the threshold of 10.

4.6 Estimation Least Square Regression

This section examines the ordinary least squares regression results These are presented in Table 4.10 as follows.

Table 4.10: Ordinary Least Squares (OLS) Regression Results

Variables	Coefficient	t-statistic	p-value
Constant	3.792	12.317	0.000***
AIACAP	0.134	3.46	0.000***
AIDAAP	0.11	2.441	0.010**
AIADAP	0.056	1.634	0.103
AIPAP	0.092	2.796	0.005***

$R = 0.783$

$R^2 = 0.633$

Adjusted $R^2 = 0.622$

Standard Error of Estimate = 0.2035

F-statistic = 2.949

Prob(F-statistic) = 0.020

Durbin-Watson Statistic = 1.993

Observations = 347

Source: Researcher's Computation using SPSS (2025)

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%.

Table 4.10 presents the results of the least squares regression analysis for the examined variables and statistical findings. The t-statistics for each coefficient are reported in parentheses below the model. The results indicate that all independent variables representing artificial intelligence in terms of artificial intelligence accounting application (AIACAP), artificial intelligence data analytic application (AIDAAP), artificial intelligence auditing application (AIADAP), and artificial intelligence predictive application (AIPAP) in relation to financial reporting quality had positive coefficients (see Appendix 4 for details).

Specifically, artificial intelligence accounting application showed a positive coefficient of 0.134 with financial reporting quality, implying that a unit increase in AIACAP could enhance financial reporting quality (FRQ) by approximately 13%. Similarly, artificial intelligence data analytic application (AIDAAP), which has a positive coefficient value of 0.110 with financial reporting quality (FRQ), indicated that a unit increase in artificial intelligence data analytic application could improve financial reporting quality by 11%. Furthermore, artificial intelligence auditing application (AIADAP) has a positive coefficient value of 0.056 with financial reporting quality (FRQ), implying that a unit increase in AIADAP could enhance financial reporting quality by approximately 6%. Likewise, artificial intelligence predictive application (AIPAP) recorded a positive coefficient value of 0.092 with financial reporting quality (FRQ), signifying that a unit increase in AIPAP could lead to an improvement in financial reporting quality by over 9%.

The positive correlation coefficient (R) of 0.783 (78.3%) suggests a strong relationship between the independent variables and financial reporting quality (FRQ). The coefficient of determination (R^2) value of 0.633 indicates that the explanatory variables account for approximately 63.3% of the variations in financial reporting quality, while the remaining 36.7% are unexplained and captured by the error term. Additionally, the adjusted coefficient of determination (R^2) value of 0.622 with financial reporting quality (FRQ) implies that, after adjusting for degrees of freedom, approximately 62.2% of the systematic variations in financial reporting quality were explained by the independent variables, which consisted of artificial intelligence accounting, data analytics, auditing, and predictive applications in relation to financial reporting quality, with the remaining 37.8% attributed to the error term.

The overall model fit, as measured by the F-statistic, yielded a value of 2.949 with a probability value of 0.020 (2%), and a standard error of regression of 0.2035. This suggests that the model is statistically significant and that a direct relationship exists between the independent variables (artificial intelligence applications) and the dependent variable (financial reporting quality). Furthermore, the Durbin-Watson statistic of 1.993 indicates the absence of autocorrelation, thereby confirming the reliability of the results for prediction and policy formulation.

4.7 Test of Hypotheses

Hypotheses previously formulated in chapter one are tested in this section. The decision rule was to accept the hypothesis formulated if it is statistically significant at 5%, otherwise we reject the hypothesis. To test the hypotheses, least square method results in Table 4.10 are used.

Test of Hypothesis One

(i) Hypothesis Formulated: $H0_1$: Artificial Intelligence accounting application has no significant influence on financial reporting quality of banks in Nigeria.

(ii) Test Statistic and Decision: Artificial intelligence accounting application (AIACAP) result in Table 4.10 which stood at positive t-statistic value of 2.480 at a probability value of 0.010 (1%), while the critical value was at 5% significance level (95% confidence). The result indicated that artificial intelligence accounting is statistically significant on financial reporting quality of deposit money bank in Nigeria.

With reference to the decision rule stated earlier, we therefore reject the hypothesis formulated suggesting that artificial intelligence accounting has significant influence on financial reporting quality among deposit money banks in Nigeria.

Test of Hypothesis Two

(i) Hypothesis Formulated: ***$H0_2$:*** Artificial Intelligence data analytics application has no significant effect on financial reporting quality among deposit money banks in Nigeria.

(ii) Test Statistic and Decision: Artificial intelligence data analytic application (AIDAAP) in Table 4.10 was at calculated t-statistics value 2.441 at probability value of 0.010(1%) while the critical probability value was 5% significance level (95% confidence). The outcome indicated that artificial intelligence data analytic is statistically significant with financial reporting quality among deposit money bank in Nigeria.

Following the decision rule, we reject hypothesis formulated indicating that artificial intelligence data analytics has significant influence on financial reporting quality among deposit money banks in Nigeria.

Test of Hypothesis Three

(i) Hypothesis Formulated: $H0_3$: Artificial Intelligence auditing application has no significant effect on financial reporting quality among deposit money banks in Nigeria.

(ii) Test Statistic and Decision: Artificial intelligence auditing application (AIADAP) statistics in Table 4.9 stood at calculated t-statistics value of (1.634) at a probability value of 0.103(10%), while the critical value was at 5% significance level (95% confidence). The result of the hypothesis test showed that artificial intelligence auditing application (AIADAP) result is statistically insignificant with financial reporting quality.

Based on the decision rule, we therefore accept the hypothesis formulated implying that artificial intelligence auditing application has no significant influence on financial reporting quality among deposit money banks in Nigeria.

Test of Hypothesis Four

(i) Hypothesis Formulated: $H0_4$: Artificial Intelligence predictive application has no significant effect on financial reporting quality among deposit money banks in Nigeria.

(ii) Test Statistic and Decision: Artificial intelligence predictive application (AIPAP) statistics in Table 4.10 stood at calculated t-statistics value of 2.796 at a probability value of 0.005(0.5%), while the critical value was at 5% significance level (95% confidence). The result of the hypothesis test showed that artificial intelligence predictive application (AIPAP) result is statistically significant with financial reporting quality.

Based on the decision rule, we therefore reject the hypothesis formulated implying that artificial intelligence predictive application has significant influence on financial reporting quality among deposit money banks in Nigeria.

4.8 Discussion of Findings

First, the finding indicated that artificial intelligence accounting has a significant positive relationship with financial reporting quality among deposit money banks in Nigeria, suggesting it is an important factor in relation to financial reporting quality. Artificial intelligence accounting with a positive coefficient value suggested that a unit increase in artificial intelligence customers can have a positive relationship with deposit money bank financial reporting quality, aligning with the *a priori* expectation. This result is consistent with previous studies of Arefeh (2024), who indicated that the use of artificial intelligence accounting software has a positive and significant effect on the accuracy and timeliness of financial reports. Al-Obaidy (2024) revealed that modern AI technologies significantly enhance accounting data accuracy in detecting and correcting errors, saving time and effort in accounting processes. Bin-Nashwan et al. (2025) found that adoption of AI-driven systems among AAFs exerted a positive impact on financial reporting accuracy and auditing efficiency, while a negative impact on information asymmetry.

Second, it was deduced that artificial intelligence data analytics have a significant effect on financial reporting quality among deposit money banks in Nigeria. The result indicated that artificial intelligence data analytics are a crucial factor influencing financial reporting quality.

Artificial intelligence data analytics which showed positive coefficient values implied the existence of a positive relationship between artificial intelligence data analytics and financial reporting quality. The result is in line with our a priori expectation, such that an increase in artificial intelligence data analytics could bring about an increase in financial reporting quality of deposit money banks. The finding is consistent with views of Shah (2025), who found that AI-driven automation and data processing applications contribute to reducing reporting delays and improving overall transparency and financial reporting quality with implications for regulators, investors, and corporate decision-makers aiming to strengthen corporate governance and stakeholder trust in the era of intelligent automation. Unuesiri and Adejuwon (2024) showed that the deployment of AI expert systems impacted the financial performance of DMBs in Nigeria positively and significantly. Oduwole & Fatogun (2023) revealed that all three variables (automation process, expert system, and intelligent agent) have a significant effect on accounting practice in deposit money bank (DMB) industries in Nigeria.

Third, it was revealed that artificial intelligence auditing application has a positive but statistically insignificant influence on financial reporting quality among deposit money banks in Nigeria. The result showed a positive coefficient of 0.056, a t-statistic of 1.634, and a probability value of 0.103, which exceeds the 5 per cent level of significance. This indicates that although artificial intelligence auditing application tends to enhance financial reporting quality, the effect is not sufficiently strong to attain statistical significance. The positive coefficient suggests that a unit increase in artificial intelligence auditing application could improve financial reporting quality by approximately 6 per cent. However, the statistical evidence implies that such improvement cannot be conclusively attributed to artificial intelligence auditing application within the sampled deposit money banks. The result is consistent with the study's a priori expectation regarding the direction of the relationship but not with respect to statistical significance. The finding, nevertheless, suggests that artificial intelligence auditing application may play a supportive role in enhancing financial reporting quality through improved transaction verification, monitoring, fraud detection, and audit efficiency. However, the relatively weak statistical effect may be attributable to the level of adoption of artificial intelligence auditing tools among deposit money banks, implementation challenges, or the continued reliance on traditional auditing procedures. The finding is in tandem with the studies of Pandey and Rana (2024), who investigated the role of artificial intelligence in accounting, auditing, and financial decision-making and found that AI applications contribute to more efficient analysis of financial information and improved reporting processes. Similarly, Thanasa et al. (2025) reported that technologies such as artificial intelligence, blockchain, and data analytics enhance transparency, efficiency, and regulatory compliance in financial reporting and auditing activities. Although the present study found a positive relationship, the absence of statistical significance suggests that greater investment and integration of AI auditing applications may be required before substantial improvements in financial reporting quality can be realised among deposit money banks in Nigeria.

Lastly, the study found that the predictive application of artificial intelligence significantly influences the financial reporting quality of deposit money banks in Nigeria. The result implied that artificial intelligence predictive applications are a strong factor enhancing the financial reporting quality of banks. An artificial intelligence predictive application, which has a positive coefficient value, indicates the existence of a positive relationship with the financial reporting quality of banks. The result is in line with our apriori expectation such that an increase in artificial intelligence predictive applications can lead to an enhancement in the financial reporting quality of deposit money banks. This buttressed the views of Chen et al. (2022), who found that AI predictive applications significantly enhance firm creativity and AI-driven decision-making, leading to improved organisational performance. In the same vein, Bag et al. (2021) revealed that artificial intelligence predictive applications contributed to enhanced financial reporting quality in terms of operational efficiency and customer satisfaction. Adeoye et al. (2023) results indicated that artificial intelligence influences audit quality and has a positive relationship with financial reporting. Parker et al. (2023) revealed that AI adoption improves the extent to which accounting estimates predict future cash flows in a firm's financial reports. Also, Ndidiamaka and Chinedu (2025) showed that the predictive nature of machine learning algorithms' artificial intelligence, the volume of data processed by AI systems, and their compatibility play a significant role in improving services. Oleimat et al. (2025) state that artificial intelligence technologies such as natural language processing and machine learning predictive applications significantly impact the accuracy and speed of financial reporting while fostering transparency and compliance.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The study was executed in five chapters. Chapter One of this thesis contains the background of the study, statement of the problem, objectives of the study, research questions, research hypothesis, scope of the study, and significance of the study. Chapter Two of this work contains the review of related literature. Chapter three was on methods and procedures employed on the study. Chapter Four focused on data presentation, analyses and interpretations. Finally, chapter five which is this chapter focused on the summary of findings, conclusion, recommendations and contributions to knowledge.

5.2 Summary of Findings

Findings of this study were summarised as follows:

1. Artificial intelligence accounting application had significant positive relationship with financial reporting quality of deposit money banks in Nigeria. The implication is that artificial intelligence accounting application is a critical enhancing factor of financial reporting quality of deposit money bank in Nigeria.
2. Artificial intelligence data analytic had significant positive relationship with the financial reporting quality of deposit money banks in Nigeria. The implication is that artificial intelligence data analytic can influence on the financial reporting quality of deposit money banks in Nigeria.
3. Artificial intelligence auditing application had no significant effect, but has positive relationship with financial reporting quality of deposit money banks in Nigeria. This implied that artificial intelligence auditing application can foster quality of financial reporting of deposit money bank in Nigeria.
4. Artificial intelligence predictive application had significant positive relationship with financial reporting quality of deposit money bank in Nigeria. This by implication is that

artificial intelligence predictive application is a crucial factor influencing financial reporting quality of deposit money banks in Nigeria

5.3 Conclusion

Artificial intelligence applications have attracted considerable attention as could enhance financial reporting quality of deposit money banks in Nigeria. This study has demonstrated that organization can achieve quality financial reporting by adopting certain technologies like artificial intelligence with its sophisticated nature in terms of machine learning, natural language processing and algorithm, capable of facilitating accounting, data analytic, auditing and predicting. The adoption of artificial intelligence (AI) in handling accounting, data analyzing, auditing and predicting financial transactions can bring about remarkable improvements in financial reporting quality which can translate into efficiency, customer service, and risk management in banks.

Having examined relevant related literature and undergone various analyses and test of hypotheses, the study revealed that that Artificial intelligence-powered accounting, data analytics and predictive application have significant positive relationship and play crucial role in enhancing financing reporting quality of deposit money banks in Nigeria. Additionally, artificial intelligence Auditing application has no significant effect but has positive relationship with financial reporting quality thereby boosting efficiency and overall quality of financial reporting. Predictive AI, especially in credit risk assessment and fraud detection which are crucial in promoting financial reporting quality, have proven to be game-changer, helping banks minimize financial losses and strengthen their financial transactions. Artificial intelligence data analytic applications focuses on describing historical data of financial transaction to support decision-making, whereas predictive AI enables banks to take proactive measures in reporting risk and business growth. Therefore, the adoption of artificial intelligence positioned in different aspects of the business operations in terms of accounting, analysing, auditing and predicting activities are aimed at enhancing financial reporting quality.

5.4 Recommendations

Based on our findings, this study recommended as follows

- **Policy Recommendations/Implications**

The policy recommendations of this study are as follows:

1. Since AI accounting application showed significant positive relationship with financial reporting quality, policymakers in accounting like Association of National Accountants of Nigeria (ANAN) and Institute of Chartered Accountants of Nigeria need to address the issues of application of artificial intelligence in handing financial transactions, documentations and preparation of accounts especially in order to promote financial reporting quality. Enhancing the skills of accounting personnel, tailoring AI accounting tools to the realities of Nigeria's business could increase relevance in financial reporting quality.
2. Banks and other organization whether private or public sector organisations in Nigeria should be encouraged to harness AI's data analytics for examining financial and employee data, trends, and behavioural patterns. The inclusion of artificial intelligence data descriptive tools can help in facilitating financial reporting quality.
3. Since artificial intelligence auditing application has proven to have positive relationship with financial reporting quality, internal and external auditors should be well trained and developed in the use of artificial intelligence for auditing especially as to promote financial reporting quality. Also, imbedding artificial intelligence auditing tools into audit practices can help in detecting errors and anomalies that would have affected financial reporting quality. Thus, banks and other organisations should invest in sophisticated AI-based auditing solutions and services in order to promote financial reporting quality for the benefit of the users of the report.

4. Since predictive AI application is a strong determinant in enhancement of financial reporting quality, banks and other organisations should give priority to adoption of artificial intelligence. Predictive models that can support risk evaluation, forecast tendencies, and provide timely alerts where there irregularities and strengthening quality of financial reporting.

- **Recommendations for Further Studies**

The following recommendations are put forward for further studies.

1. Since this study focused on the banking sector, we expected further studies to focus on the insurance, manufacturing, oil and gas etc by undertaking analysis using regression.
2. Further studies should employ content analysis since this study used questionnaire as research instrument and analyse using panel data if possible.
3. Further studies should introduce more variables to proxy artificial intelligence and re-examine this study.

5.5 Contributions to Knowledge

The study has contributed to knowledge by investigating on the relationship between artificial intelligence applications and financial reporting quality among deposit money banks in Nigeria using artificial intelligence accounting, data analytics, auditing and predictive applications as proxy variables to artificial intelligence which have not been used by extant studies in Nigeria. It also contributed to knowledge by showing that artificial intelligence applications in accounting, data analytics and predictive analytics are critical enhancing factors of financial reporting quality of deposit money banks in Nigeria. Furthermore, it contributed to knowledge by highlighting that artificial intelligence auditing application does not have significant effect on the quality of financial reports in deposit money banks in Nigeria but can only foster the quality of their financial reports.

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APPENDIX I

Artificial Intelligence and Financial Reporting Quality

SECTION I

1. Age: ____

2. Sex: M [ ] F[ ]

3. Educational level: O' Level [ ] Diploma [ ] Bsc [ ] Msc [ ] Phd [ ]

4. Name of Bank: ____

5. Religion: Christianity [ ] Islam[ ] African traditional religion[ ]

Others ________

SECTION II

Please tick () as appropriate using the following keys:

SA = Strongly Agree

A = Agree

U = Undecided

D = Disagree

SD = Strongly Disagree

S/N	Statement Questions	SD	D	U	A	SA
	Section A: Financial Reporting Quality					
1.	Quality financial report facilitates relevance by the stakeholders					
2.	Quality financial report promotes faithful representation of report by the interest of users.					
3.	Quality financial report facilitates comparability of the report by the stakeholders.					
4.	Quality financial report can promotes reliability of report by the					

	stakeholders.					
5.	Quality financial report facilitates timeliness in informed decision making by users.					
	Section B: Artificial Intelligence Accounting application and Financial Reporting Quality.					
6	Artificial Intelligence can help generate relevant and reliable data for preparation of accounts in my bank					
7.	Artificial Intelligence can assist in generating information and evidences for preparation of accounts without delay in my bank					
8.	Artificial Intelligence can help in timely posting of financial transactions that can be relied on by stakeholders of my bank					
9.	Artificial Intelligence can facilitate reconciliation of financial statements that can be reliable by stakeholders of my bank					
10.	Artificial Intelligence can assist in balancing of transactions timely without errors in my bank					
	Section C: Artificial Intelligence data Analytics application and Financial Reporting Quality					
11.	Artificial intelligence application in analysing past financial data can foster quality report in my bank.					
12.	Artificial intelligence application in describing financial data estimated can help to evaluate quality report in my bank.					
13.	Artificial intelligence application in analysing present financial data can help to improve quality financial report in my bank.					
14.	Use of artificial intelligence in analysing transactions data patterns can assist to make informed decision that can enhance					

	quality financial report in my bank					
15	Artificial intelligence application in analyzing various books of accounts prepared can enhance quality financial report in my bank					
	Section D: Artificial Intelligence Auditing application and Financial Reporting Quality.					
16	Use of Artificial Intelligence in examining accuracy of financial transactions data can help in facilitating quality financial report in my bank.					
17	Use of Artificial Intelligence in auditing evidences of financial transactions can help in ensuring quality financial report in my bank					
18	Use of Artificial Intelligence in auditing entries and posting of financial transaction can foster quality financial report in my bank.					
19	Use of Artificial Intelligence in auditing promotes timeliness in financial report in my bank					
20	Artificial intelligence auditing application of various books of accounts can foster quality financial report for the interest of stakeholders of my bank.					
	Section E: Artificial Intelligence Predictive application and Financial Reporting Quality					
21.	Artificial Intelligence predictive application can foster relevance of financial report for the interest of stakeholders of my bank					
22.	Artificial Intelligence predictive application can facilitate					

	faithful representation of financial report for the interest of stakeholders of my bank					
23.	Artificial Intelligence predictive application can promote comparability of financial report for the interest of stakeholders of my bank					
24.	Artificial intelligence predictive applications can help to detect irregularities and promote quality financial report of my bank					
25.	Artificial intelligence predictive application can foster quality of financial report of my bank					

APPENDIX II

RESULTS

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Frequencies Notes

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N	Valid	347	347	347	346	347	347
	Missing	0	0	0	1	0	0

SEX

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	191	55.0	55.0	55.0
	2	156	45.0	45.0	100.0
	Total	347	100.0	100.0	

MARITAL STATUS

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	91	26.2	26.2	26.2
	2	256	73.8	73.8	100.0
	Total	347	100.0	100.0	

AGE

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	165	47.6	47.6	47.6
	2	126	36.3	36.3	83.9
	3	39	11.2	11.2	95.1
	4	17	4.9	4.9	100.0
	Total	347	100.0	100.0	

EDUCATIONAL QUALIFICATION

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	79	22.8	22.8	22.8
	2	66	19.0	19.1	41.9
	3	171	49.3	49.4	91.3
	4	25	7.2	7.2	98.6
	5	5	1.4	1.4	100.0
	Total	346	99.7	100.0	
Missing	System	1	.3		
Total		347	100.0		

YEARS OF EXPERIENCE

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	245	70.6	70.6	70.6
	2	52	15.0	15.0	85.6
	3	35	10.1	10.1	95.7
	4	14	4.0	4.0	99.7
	5	1	.3	.3	100.0
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		Q1	Q2	Q3	Q4	Q5
N	Valid	347	347	347	347	347
	Missing	0	0	0	0	0
Mean		4.72	4.75	4.53	4.56	4.55
Std. Deviation		.467	.515	.523	.536	.559

Q1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	1	.3	.3	.3
	4	93	26.8	26.8	27.1
	5	253	72.9	72.9	100.0
	Total	347	100.0	100.0	

Q2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	2	2	.6	.6	.9
	3	1	.3	.3	1.2
	4	76	21.9	21.9	23.1
	5	267	76.9	76.9	100.0
	Total	347	100.0	100.0	

Q3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3	4	1.2	1.2	1.2
	4	156	45.0	45.0	46.1
	5	187	53.9	53.9	100.0
	Total	347	100.0	100.0	

Q4

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3	7	2.0	2.0	2.0
	4	139	40.1	40.1	42.1
	5	201	57.9	57.9	100.0
	Total	347	100.0	100.0	

Q5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	3	5	1.4	1.4	1.7
	4	143	41.2	41.2	42.9
	5	198	57.1	57.1	100.0
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Frequencies

Statistics

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	Missing	0	0	0	0	0
Mean		4.58	4.45	4.52	4.50	4.49
Std. Deviation		.632	.684	.550	.586	.561

Frequency Table

Q6

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	2	.6	.6	.6
	2	3	.9	.9	1.4
	3	6	1.7	1.7	3.2
	4	116	33.4	33.4	36.6
	5	220	63.4	63.4	100.0
	Total	347	100.0	100.0	

Q7

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	5	1.4	1.4	1.4
	3	23	6.6	6.6	8.1
	4	131	37.8	37.8	45.8
	5	188	54.2	54.2	100.0
	Total	347	100.0	100.0	

Q8

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	1	.3	.3	.3
	3	6	1.7	1.7	2.0
	4	150	43.2	43.2	45.2

	5	190	54.8	54.8	100.0
	Total	347	100.0	100.0	

Q9

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	2	2	.6	.6	.9
	3	4	1.2	1.2	2.0
	4	156	45.0	45.0	47.0
	5	184	53.0	53.0	100.0
	Total	347	100.0	100.0	

Q10

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	3	5	1.4	1.4	1.7
	4	162	46.7	46.7	48.4
	5	179	51.6	51.6	100.0
	Total	347	100.0	100.0	

FREQUENCIES VARIABLES=Q11 Q12 Q13 Q14 Q15
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Frequencies

Statistics

		Q11	Q12	Q13	Q14	Q15
N	Valid	347	347	347	346	347
	Missing	0	0	0	1	0
Mean		4.55	4.69	4.55	4.57	4.60
Std. Deviation		.573	.527	.558	.541	.577

Q11

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	2	2	.6	.6	.9
	3	2	.6	.6	1.4
	4	141	40.6	40.6	42.1
	5	201	57.9	57.9	100.0
	Total	347	100.0	100.0	

Q12

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	2	1	.3	.3	.6
	3	2	.6	.6	1.2
	4	96	27.7	27.7	28.8
	5	247	71.2	71.2	100.0
	Total	347	100.0	100.0	

Q13

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	2	1	.3	.3	.6
	3	2	.6	.6	1.2
	4	145	41.8	41.8	42.9
	5	198	57.1	57.1	100.0
	Total	347	100.0	100.0	

Q14

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	1	.3	.3	.3

	3	5	1.4	1.4	1.7
	4	136	39.2	39.3	41.0
	5	204	58.8	59.0	100.0
	Total	346	99.7	100.0	
Missing	System	1	.3		
Total		347	100.0		

Q15

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	2	.6	.6	.6
	3	10	2.9	2.9	3.5
	4	113	32.6	32.6	36.0
	5	222	64.0	64.0	100.0
	Total	347	100.0	100.0	

FREQUENCIES VARIABLES=Q16 Q17 Q18 Q19 Q20
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Frequencies

[DataSet1]

Statistics

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N	Valid	347	347	347	347	347
	Missing	0	0	0	0	0
Mean		4.55	4.59	4.59	4.50	4.44
Std. Deviation		.589	.553	.548	.576	.807

Frequency Table

Q16

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	2	2	.6	.6	.9

	3	5	1.4	1.4	2.3
	4	136	39.2	39.2	41.5
	5	203	58.5	58.5	100.0
	Total	347	100.0	100.0	

Q17

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	3	5	1.4	1.4	1.7
	4	128	36.9	36.9	38.6
	5	213	61.4	61.4	100.0
	Total	347	100.0	100.0	

Q18

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	3	4	1.2	1.2	1.4
	4	131	37.8	37.8	39.2
	5	211	60.8	60.8	100.0
	Total	347	100.0	100.0	

Q19

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	.3	.3	.3
	2	2	.6	.6	.9
	3	2	.6	.6	1.4
	4	159	45.8	45.8	47.3
	5	183	52.7	52.7	100.0
	Total	347	100.0	100.0	

Q20

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	5	1.4	1.4	1.4
	2	4	1.2	1.2	2.6
	3	28	8.1	8.1	10.7
	4	106	30.5	30.5	41.2
	5	204	58.8	58.8	100.0
	Total	347	100.0	100.0	

FREQUENCIES VARIABLES=Q21 Q22 Q23 Q24 Q25

Statistics

		Q21	Q22	Q23	Q24	Q25
N	Valid	347	347	347	347	347
	Missing	0	0	0	0	0
Mean		4.43	3.83	4.56	4.67	4.47
Std. Deviation		.720	1.354	.700	.567	.823

Q21

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	3	.9	.9	.9
	2	5	1.4	1.4	2.3
	3	14	4.0	4.0	6.3
	4	142	40.9	40.9	47.3
	5	183	52.7	52.7	100.0
	Total	347	100.0	100.0	

Q22

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	34	9.8	9.8	9.8
	2	45	13.0	13.0	22.8
	3	12	3.5	3.5	26.2

	4	110	31.7	31.7	57.9
	5	146	42.1	42.1	100.0
	Total	347	100.0	100.0	

Q23

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	2	.6	.6	.6
	2	7	2.0	2.0	2.6
	3	9	2.6	2.6	5.2
	4	106	30.5	30.5	35.7
	5	223	64.3	64.3	100.0
	Total	347	100.0	100.0	

Q24

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	2	.6	.6	.6
	3	11	3.2	3.2	3.7
	4	88	25.4	25.4	29.1
	5	246	70.9	70.9	100.0
	Total	347	100.0	100.0	

Q25

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	5	1.4	1.4	1.4
	2	12	3.5	3.5	4.9
	3	8	2.3	2.3	7.2
	4	113	32.6	32.6	39.8
	5	209	60.2	60.2	100.0
	Total	347	100.0	100.0	

CORRELATIONS
/VARIABLES=FRQ AIACAP AIDAAP AIADAP AIPAP
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Correlations
[DataSet1]
Correlations

		FRQ	AIACAP	AIDAAP	AIADAP	AIPAP
FRQ	Pearson Correlation	1	.014	.058	.102	.037
	Sig. (2-tailed)		.800	.284	.057	.489
	N	347	347	347	347	347
AIACAP	Pearson Correlation	.014	1	.049	-.010	.153**
	Sig. (2-tailed)	.800		.359	.860	.004
	N	347	347	347	347	347
AIDAAP	Pearson Correlation	.058	.049	1	.158**	.084
	Sig. (2-tailed)	.284	.359		.003	.118
	N	347	347	347	347	347
AIADAP	Pearson Correlation	.102	-.010	.158**	1	-.027
	Sig. (2-tailed)	.057	.860	.003		.617
	N	347	347	347	347	347
AIPAP	Pearson Correlation	.037	.153**	.084	-.027	1
	Sig. (2-tailed)	.489	.004	.118	.617	
	N	347	347	347	347	347

**. Correlation is significant at the 0.01 level (2-tailed).

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DATASET NAME DataSet1 WINDOW=FRONT.

REGRESSION

/MISSING LISTWISE

/STATISTICS COEFF OUTS R ANOVA COLLIN TOL

/CRITERIA=PIN(.05) POUT(.10)

/NOORIGIN

/DEPENDENT FRQ

/METHOD=ENTER AIACAP AIDAAP AIADAP AIPAP

/RESIDUALS DURBIN.

Regression

[DataSet1]

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AIPAP, AIADAP, AIDAAP, AIACAP	.	Enter

a. Dependent Variable: FRQ

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.783[a]	.633	.622	.2034936	1.993

a. Predictors: (Constant), AIPC, AIADC, AIDAC, AIACC

b. Dependent Variable: FRQ

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	.489	4	.122	2.949	.020[b]
	Residual	14.162	342	.041		
	Total	14.651	346			

a. Dependent Variable: FRQ

b. Predictors: (Constant), AIPAP, AIADAP, AIDAAP, AIACAP

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.792	.308		12.317	.000		
	AIACAP	.134	.039	.025	3.460	.000	.845	1.059
	AIDAAP	.110	.045	.024	2.441	.010	.877	1.024
	AIADAP	.056	.034	.087	1.634	.103	.791	1.009
	AIPAP	.092	.033	.153	2.796	.005	.845	1.058

a. Dependent Variable: FRQ

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	AIACAP	AIDAAP	AIADAP	AIPAP
1	1	4.986	1.000	.00	.00	.00	.00	.00
	2	.006	28.929	.00	.02	.00	.41	.45
	3	.004	36.298	.00	.46	.04	.24	.46
	4	.003	41.241	.01	.39	.56	.15	.01
	5	.001	71.330	.99	.14	.40	.20	.08

a. Dependent Variable: FRQ

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.437915	4.697590	4.620749	.0375748	347
Residual	-1.0161300	.4353647	0E-7	.2023139	347
Std. Predicted Value	-4.866	2.045	.000	1.000	347
Std. Residual	-4.993	2.139	.000	.994	347

a. Dependent Variable: FRQ