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RESEARCH ARTICLE

Artificial Intelligence Adoption and Perceived Financial Reporting Accuracy: Evidence from Accounting Professionals in Nigeria

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Abstract

This study examines the association between AI adoption and perceived financial reporting accuracy among accounting professionals in Nigeria. A quantitative cross-sectional survey design was employed using questionnaire data collected from 384 accounting professionals, including accountants, auditors, financial analysts, finance managers, chief financial officers, accounting consultants, and other professionals involved in financial reporting and accounting information systems. Data were analyzed using descriptive statistics, reliability and validity tests, Pearson correlation analysis, and regression analysis. The findings indicate that AI adoption is positively and significantly associated with perceived financial reporting accuracy. AI adoption is also positively associated with perceived error reduction, reporting timeliness and efficiency, and accounting information systems quality. Organizational readiness is positively associated with AI utilization, while AI adoption challenges are negatively associated with AI utilization. In the main regression model, AI adoption, organizational readiness, and accounting information systems quality significantly predicted perceived financial reporting accuracy, whereas AI adoption challenges had a negative but statistically weaker association when the other predictors were included. The study contributes perception-based evidence from Nigeria and shows that AI-enabled accounting technologies may strengthen perceived reporting processes

Keywords: Artificial Intelligence, Reporting Accuracy, Accounting Information Systems, Organizational Readiness, Emerging Economy Context, Reporting Quality

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1. Introduction

Artificial Intelligence (AI) is increasingly reshaping accounting work by automating routine processes, supporting transaction analysis, strengthening anomaly detection, improving forecasting, and enhancing the functionality of accounting information systems. In accounting and auditing, cognitive technologies are increasingly capable of automating structured activities while also supporting professional analysis and judgment in less routine tasks (Kokina & Davenport, 2017). In financial reporting, these capabilities may improve perceived accuracy, timeliness, reliability, and usefulness of accounting information. However, the benefits of AI adoption are not automatic. They depend on user acceptance, system quality, organizational readiness, data governance, technical competence, cybersecurity controls, and the ability of organizations to overcome implementation challenges. These issues are particularly important in Nigeria and comparable emerging-economy settings, where firms may face infrastructure constraints, skill shortages, limited financial resources, and evolving regulatory environments.

Financial reporting accuracy remains central to organizational transparency, regulatory compliance, investor confidence, corporate governance, and stakeholder decision-making. Users of financial statements rely on reliable financial reports to assess organizational performance, evaluate risk, and make informed economic decisions. However, reporting processes may be weakened by manual errors, delayed transaction processing, inconsistent data entry, fragmented systems, estimation uncertainty, and limited capacity to detect anomalies across large volumes of financial data.

The relevance of AI adoption is particularly important in Nigeria, where organizations are increasingly investing in digital transformation while also facing constraints related to technological infrastructure, skilled personnel, implementation cost, data quality, cybersecurity, and regulatory development. Recent regional evidence on fintech, AI, and digital transformation in financial institutions similarly shows that emerging-market organizations are increasingly exposed to AI, machine learning, fintech platforms, and digital payment systems, yet the realized value of these technologies depends on institutional readiness, infrastructure, skills, and governance capacity (Alslaibi, 2024; Al-Alawnh et al., 2026; Latiff et al., 2025). Although AI-enabled accounting technologies may support reporting efficiency and reliability, their perceived value depends on organizational readiness, accounting information systems quality, management support, employee competence, and the ability to manage implementation challenges.

Despite the increasing use of AI in accounting, empirical evidence on its relationship with financial reporting outcomes remains limited, especially from the perspective of accounting professionals in Nigeria. Much of the existing literature has focused on auditing applications, forecasting models, automation, and conceptual discussions of AI in accounting. Bibliometric evidence in the accounting information systems field also indicates that AI, machine learning, blockchain, cloud computing, robotic process automation, and data analytics have become visible research streams, but empirical work on how these technologies affect AIS performance, acceptance, and reporting outcomes remains underdeveloped (Al-Khoury et al., 2025). In addition, recent evidence on AI and financial statement transparency indicates that AI-based disclosure benefits depend on the reliability and stability of accounting information systems, reinforcing the need to examine AI adoption together with AIS quality rather than treating AI as an isolated technology (Alslaibi et al., 2025).

This distinction is important because the present study examines perceived financial reporting accuracy rather than objectively verified financial reporting quality. The survey responses reflect the judgments and professional experiences of accounting professionals, not direct evidence of fewer restatements, audit adjustments, internal control weaknesses, or actual reporting errors. Therefore, the study does not claim that AI adoption objectively eliminates reporting errors; rather, it examines whether accounting professionals perceive AI-supported systems as improving reporting-related outcomes.

Accordingly, this study examines the association between AI adoption and perceived financial reporting accuracy among accounting professionals in Nigeria. Specifically, it assesses the relationship between AI adoption and perceived reporting accuracy, perceived error reduction, reporting timeliness and efficiency, accounting information systems quality, and AI utilization. It also examines the roles of organizational readiness and AI adoption challenges in shaping the use of AI in accounting practices.

The study contributes to the literature on AI adoption, accounting information systems, and financial reporting quality in three ways. First, it provides perception-based empirical evidence from Nigeria, an important emerging-economy context. Second, it integrates technology acceptance, organizational readiness, information systems success, and behavioral-governance fit perspectives to explain how AI adoption relates to perceived reporting outcomes. Third, it offers practical insights for organizations, accounting professionals, regulators, and policymakers seeking to use AI responsibly in accounting and financial reporting. The remainder of the manuscript reviews the literature and hypotheses, explains the methodology, presents the results, discusses the findings, and concludes with implications, limitations, and future research directions.

2. Literature Review and Hypothesis Development

Artificial Intelligence (AI) is increasingly reshaping accounting work by autzmating routine processes, supporting transaction analysis, strengthening anomaly detection, improving forecasting, and enhancing the functionality of accounting information systems. In financial reporting, these capabilities are expected to improve the perceived accuracy, timeliness, reliability, and usefulness of accounting information. However, the benefits of AI adoption are not automatic. They depend on user acceptance, system quality, organizational readiness, data governance, technical competence, cybersecurity controls, and the ability of organizations to overcome implementation challenges. These issues are particularly important in emerging economies, where firms may face infrastructure constraints, skill shortages, limited financial resources, and evolving regulatory environments.

This study is grounded in three complementary theoretical perspectives: the Technology Acceptance Model (TAM), the Technology-Organization-Environment (TOE) framework, and the DeLone and McLean Information Systems Success Model. TAM explains why accounting professionals may use AI when they perceive it as useful and easy to apply in accounting tasks (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). TOE explains why adoption and utilization depend on technological, organizational, and environmental conditions, including infrastructure, management support, resources, readiness, industry pressure, and regulatory context (Tornatzky & Fleischer, 1990; Badghish & Soomro, 2024; Hossain et al., 2024). The DeLone and McLean model links information-system success to system quality, information quality, service quality, use, user satisfaction, and net benefits, making it relevant for explaining how AI-enabled accounting systems may shape perceived reporting outcomes (DeLone & McLean, 1992, 2003; Brahmantyo et al., 2023; Gormantara & Elisabeth, 2023).

To strengthen the governance and behavioral dimension of the framework, the study also draws on Behavioral-Governance Fit Theory (BGFT). BGFT argues that organizational outcomes are shaped by the fit between internal behavioral dynamics and governance quality rather than by either behavioral or structural conditions alone (Alslaibi et al., 2026). In the present study, this perspective supports the expectation that AI adoption is more likely to be perceived as improving reporting outcomes when organizational readiness, governance safeguards, AIS reliability, and users' accounting routines are aligned.

2.1 AI Adoption and Perceived Financial Reporting Accuracy

AI adoption is expected to be positively associated with perceived financial reporting accuracy because AI-enabled systems can process large volumes of accounting data, automate transaction classification, identify unusual patterns, validate entries, and support more consistent reporting judgments. In accounting contexts, perceived accuracy refers to the extent to which accounting professionals believe that AI-supported systems improve the correctness, completeness, and reliability of financial information. From the TAM perspective, AI adoption is likely to increase when accounting professionals perceive AI as useful for improving reporting outcomes and reducing manual effort (Davis, 1989; Venkatesh & Davis, 2000). From the DeLone and McLean perspective, AI can support perceived reporting accuracy when it strengthens information quality, system reliability, and decision usefulness (DeLone & McLean, 1992, 2003).

Prior research generally supports the positive relationship between advanced digital technologies and financial reporting quality. Saleh et al. (2022) show that big data analytics can support financial reporting quality by improving analytical capacity and the ability to process large datasets. Younis (2020) argues that big data analytics enhances financial reporting quality by improving relevance, reliability, predictive ability, and real-time access to financial information. Hung et al. (2023) demonstrate that machine-learning approaches can be used to assess financial reporting quality and identify its determinants. More directly, Alslaibi et al. (2025) show that AI technologies can improve financial statement transparency through voluntary disclosure, especially when AIS reliability is strong, while Hasan Samara et al. (2025) link accounting culture and governance mechanisms to financial reporting quality in Arab banking contexts. These studies reinforce the argument that AI-related reporting benefits depend not only on automation, but also on reliable systems, governance safeguards, and the professional environment in which accounting information is produced.

Studies in accounting and auditing further support this argument. Hasan (2022) notes that AI applications in accounting and auditing can support automated analysis, risk identification, and decision support.Earlier auditing research similarly explains that AI can formalize selected audit procedures and supplement the professional workforce, particularly when large datasets exceed the practical limits of conventional manual examination (Issa et al,2016). Adeoye et al. (2023) argue that AI can improve audit quality by enabling auditors and accountants to analyze large datasets and detect anomalies more effectively. Dahiyat (2022) finds that robotic process automation can support audit quality, while Ditkaew and Suttipun (2023) show that audit data analytics can influence audit quality and review continuity. Research on digital accounting also indicates that AI, data analytics, cloud systems, and machine learning can enhance the efficiency and accuracy of accounting information systems (Prasetianingrum & Sonjaya, 2024; Chu & Yong, 2021; Balios et al., 2020).

Nevertheless, the literature also provides contrasting and mixed evidence. AI does not guarantee accurate reporting if data inputs are incomplete, biased, poorly structured, or weakly governed (Hasan, 2022; Anica-Popa et al., 2024). Algorithmic opacity, cybersecurity threats, and overreliance on automated outputs may weaken professional skepticism and increase model-related risk (Mogaji et al., 2024; Michael & Dixon, 2019). The use of AI in assurance activities also creates ethical concerns involving accountability, transparency, privacy, bias, and the appropriate division of responsibility between professionals and automated systems (Munoko et al., 2020). AIS studies also show that technology adoption alone may not improve financial-reporting quality unless supported by internal controls, human competence, and organizational commitment (Arfismanda et al., 2021; Kasdan, 2023; Suludin et al., 2022). These mixed findings are important because they suggest that AI may improve perceived accuracy only when accounting professionals trust the system, understand its outputs, and operate within a sound control environment.

Despite these concerns, the hypothesis remains justified in the Nigerian context. In such settings, accounting departments may still rely on manual processes, fragmented accounting systems, delayed reconciliations, and limited analytical capacity. AI adoption can therefore be perceived as improving financial reporting accuracy by reducing manual intervention, improving data validation, strengthening anomaly detection, and increasing confidence in accounting outputs (Badghish & Soomro, 2024; Anh et al., 2024; Saleh et al., 2022). Therefore, the following hypothesis is proposed:

H1: Artificial Intelligence adoption is positively associated with perceived financial reporting accuracy among accounting professionals in Nigeria.

2.2 AI Adoption and Perceived Reduction of Accounting and Financial Reporting Errors

AI adoption is also expected to be positively associated with perceived reduction of accounting and financial reporting errors. Errors in accounting may arise from manual data entry, misclassification, delayed reconciliation, duplicated transactions, weak validation procedures, and inconsistent application of reporting rules. AI-enabled systems can reduce these risks by automating repetitive tasks, detecting unusual patterns, flagging exceptions, and improving the consistency of accounting procedures. Under TAM, perceived error reduction reflects perceived usefulness because the technology helps professionals perform accounting tasks more accurately and efficiently (Davis, 1989; Venkatesh et al., 2003). Under the DeLone and McLean model, lower perceived error exposure may result from higher system quality, information quality, and user satisfaction (DeLone & McLean, 1992, 2003).

Prior studies support this relationship. Tiron-Tudor et al. (2024) explain that robotic process automation is transforming accounting and auditing services by automating routine activities and improving process performance. RPA is particularly applicable to repetitive, manual, and rules-based procedures, allowing professionals to redirect attention toward activities requiring interpretation and judgment (Moffitt et al., 2018). Early evidence from accounting organizations further indicates that successful automation requires appropriate process selection, coordination between accounting and technology personnel, and redesign of existing workflows (Kokina & Blanchette, 2019). Mokoginta et al. (2024) find that RPA improves the efficiency of accounting processes in Indonesia and is associated with reduced errors and better process outcomes. Dahiyat (2022) also links RPA implementation to audit quality, while Xu (2024) highlights the role of automation technologies in streamlining repetitive accounting tasks and reducing errors. Prasetianingrum and Sonjaya (2024) argue that digital accounting and AIS evolution are closely connected to improved accuracy, productivity, and automation of financial-management tasks.

Audit, internal-control, and analytics studies provide further support. Ditkaew and Suttipun (2023) suggest that audit data analytics improves audit quality and enables auditors to examine transactions more effectively. Chu and Yong (2021) argue that data analytics allows auditors and accountants to focus on exception reporting and identify outliers in risk areas. Balios et al. (2020) explain that big data and data analytics create opportunities for improving external auditing by expanding the scope of analysis and reducing dependence on traditional sampling. Evidence from governance and control research also indicates that audit quality and fraud prevention depend on board expertise, internal control mechanisms, and the effective use of structured control systems (Aljarrah & Alslaibi, 2025; Alslaibi et al., 2026). This supports the view that AI-enabled error reduction should be interpreted as a controlled accounting process rather than a purely technical outcome.

However, AI may also create new categories of error. Poor model design, weak data governance, insufficient user training, algorithmic bias, and lack of explainability can produce misleading outputs (Hasan, 2022; Anica-Popa et al., 2024). Some research also warns that automation can shift error risk from human processing errors to system configuration errors, data-quality errors, and model-risk errors (Michael & Dixon, 2019; Mogaji et al., 2024). Furthermore, AIS-related studies show mixed results, indicating that the effect of information systems on reporting quality depends on internal controls, employee competence, and organizational commitment (Arfismanda et al., 2021; Kasdan, 2023; Yusnita et al., 2024).

The hypothesis remains justified because this study examines perceived error reduction among accounting professionals. In Nigeria, where accounting processes may involve manual handling, limited automation, and resource constraints, professionals may perceive AI adoption as reducing routine errors and improving the reliability of accounting outputs. Therefore:

H2: Artificial Intelligence adoption is positively associated with perceived reduction of accounting and financial reporting errors.

2.3 AI Adoption and Perceived Timeliness and Efficiency of Financial Reporting Processes

AI adoption is expected to be positively associated with the timeliness and efficiency of financial reporting processes. Timeliness refers to the ability to generate and communicate accounting information quickly enough to support decision-making, compliance, and stakeholder reporting. Efficiency refers to reducing the time, cost, and effort required to complete accounting and reporting tasks. AI can improve these outcomes by automating reconciliations, accelerating journal-entry processing, supporting real-time analytics, improving workflow integration, and reducing the manual workload of accounting professionals.

TAM provides a strong theoretical basis for this relationship because faster and more efficient reporting represents perceived usefulness (Davis, 1989; Venkatesh & Davis, 2000). TOE also supports the relationship because technological capabilities, organizational readiness, and environmental pressures may influence whether AI is successfully embedded in reporting processes (Tornatzky & Fleischer, 1990; Badghish & Soomro, 2024). The DeLone and McLean model further suggests that improved system quality and information quality can lead to greater system use and net benefits (DeLone & McLean, 1992, 2003).

Prior research supports the expectation that AI and related digital technologies improve reporting efficiency. Tiron-Tudor et al. (2024) show that RPA is transforming accounting and auditing services by improving operational performance. Framework-based research also shows that RPA can be incorporated into audit workflows to automate structured procedures, improve processing consistency, and support more continuous forms of assurance (Huang & Vasarhelyi, 2019). Mokoginta et al. (2024) find that RPA improves accounting-process efficiency in Indonesia. Younis (2020) argues that big data analytics supports real-time access, predictive analysis, and faster financial-reporting processes. Saleh et al. (2022) also link big data analytics to improved reporting quality and analytical capability. Recent fintech and emerging-technology studies similarly indicate that AI, machine learning, blockchain, digital payments, cloud systems, and analytics are reshaping financial-sector operations and accounting information systems, particularly in emerging-market settings (Al-Alawnh et al., 2026; Al-Khoury et al., 2025; Latiff et al., 2025).

In the broader organizational context, Badghish and Soomro (2024) show that AI adoption can improve productivity and business performance, while Hossain et al. (2024) emphasize organizational readiness as a condition for adopting AI and big data analytics.

Digital audit and analytics research provides additional support. Ditkaew and Suttipun (2023) show that audit data analytics can support audit quality and continuity, while Chu and Yong (2021) argue that data analytics enables accountants and auditors to improve risk assessment and exception reporting.However, the value of automation depends on systematically identifying which tasks are technically feasible and organizationally appropriate for automation, rather than applying bots indiscriminately across the reporting process (Eulerich et al., 2022). Balios et al. (2020) explain that big data and analytics change the external audit process by expanding analytical scope and supporting more efficient procedures. Michael and Dixon (2019) discuss audit data analytics in relation to voluntary disclosures and the audit expectations gap, indicating that analytics can influence assurance and reporting perceptions.

Nevertheless, the literature also warns that efficiency gains may not occur immediately. AI implementation may initially increase complexity because organizations must redesign processes, train staff, integrate systems, and manage new forms of technological risk (Hasan, 2022; Romana et al., 2023; Anica-Popa et al., 2024). RPA implementation likewise requires process standardization, suitable task selection, technical integration, governance arrangements, and continuing maintenance, meaning that expected efficiency gains depend heavily on implementation quality (Hofmann et al., 2020). Sudaryanto et al. (2023) find that perceived usefulness and perceived ease of use influence AI adoption, but technology readiness and digital competence may not always have significant effects, suggesting mixed evidence on readiness-related drivers. Mogaji et al. (2024) also question whether traditional TAM is sufficient in the generative AI era because trust, explainability, and user expectations may shape adoption beyond usefulness and ease of use.

Despite these mixed findings, the hypothesis remains justified in the context of accounting professionals in Nigeria. Where financial reporting is delayed by manual procedures, fragmented systems, and limited accounting resources, AI adoption can be perceived as improving reporting timeliness and efficiency. Therefore:

H3: Artificial Intelligence adoption is positively associated with perceived timeliness and efficiency of financial reporting processes.

2.4 Organizational Readiness and AI Utilization in Accounting Functions

Organizational readiness refers to the extent to which an organization possesses the infrastructure, resources, leadership support, technical skills, data quality, cybersecurity capacity, and change-management capability required for sustained AI utilization. TOE provides the most direct theoretical basis for this hypothesis because organizational conditions are central to technology adoption and implementation success (Tornatzky

& Fleischer, 1990; Badghish & Soomro, 2024). TAM also supports the relationship indirectly because organizational support, training, and technical resources can increase perceived ease of use and perceived usefulness among accounting professionals (Davis, 1989; Venkatesh et al., 2003). From a Behavioral-Governance Fit Theory perspective, readiness also reflects the alignment between technological capability, governance arrangements, and internal behavioral routines; without this fit, AI adoption may remain symbolic rather than operationally embedded (Alslaibi et al., 2026).

Prior research supports the importance of readiness. Organizational AI readiness is multidimensional and includes strategic alignment, resources, knowledge, data, technology infrastructure, governance, and organizational culture rather than merely the acquisition of AI software (Jöhnk et al., 2021). Badghish and Soomro (2024) apply the TOE framework to AI adoption by SMEs and show that technological and organizational factors are central to AI adoption and sustainable performance. Hossain et al. (2024) examine AI and big data analytics adoption from an organizational-readiness perspective, emphasizing the importance of organizational capability, resources, and preparedness. Consistent with this capability perspective, organizations must combine tangible resources, human expertise, coordination mechanisms, and data-related capabilities to translate AI investments into improved organizational outcomes (Mikalef & Gupta ,2021). Anh et al. (2024) find that technology readiness affects AI adoption in accounting and auditing in Vietnam through perceived usefulness and perceived ease of use. In emerging-market governance research, AI has also been shown to strengthen the relationship between corporate governance and firm performance, indicating that digital capability can work as a complementary mechanism when organizational structures are supportive (Amarna et al., 2025). Abdo-Salloum and Al-Mousawi (2025) similarly examine technology readiness, perceptions, and digital competence in relation to AI adoption in accounting education.

Accounting-specific studies further reinforce this argument. Al Wael et al. (2023) examine factors influencing AI adoption in the accounting profession in Kuwait's public sector and highlight the relevance of organizational and individual adoption factors. Sudaryanto et al. (2023) show that perceived usefulness and ease of use influence AI adoption among accounting students, while Stanciu et al. (2020) argue that accounting education must adjust to digital transformation because accountants increasingly require IT-related skills. Romana et al. (2023) similarly argue that AI changes accountants' professional roles and requires new knowledge, flexibility, and technological mastery.

However, readiness does not guarantee successful implementation. Some organizations may have financial resources but lack data governance, user commitment, cybersecurity controls, or integration capacity (Hasan, 2022; Anica-Popa et al., 2024). Other organizations may adopt AI symbolically without embedding it into accounting workflows. Research also indicates that digital competence and technology readiness may not always have statistically significant effects on AI adoption, depending on context and user group (Sudaryanto et al., 2023). Moreover, implementation barriers such as cost, resistance to change, lack of government support, and weak infrastructure can limit the expected benefits of digital transformation (Ahmad & Nasseredine, 2019; Okoye et al., 2024).

The hypothesis remains justified because AI utilization in accounting requires more than software acquisition. In Nigeria, sustained use of AI-supported accounting tools depends on whether organizations have adequate infrastructure, trained professionals, reliable data, management commitment, and cybersecurity safeguards. Therefore:

H4: Organizational readiness is positively associated with AI utilization in accounting functions.

2.5 AI Adoption and Accounting Information Systems Quality

AI adoption is expected to be positively associated with accounting information systems quality. AIS quality refers to the extent to which accounting systems generate accurate, reliable, timely, complete, and useful information for reporting and decision-making. AI can improve AIS quality by enhancing data validation, transaction classification, anomaly detection, predictive analytics, workflow automation, and reporting integration. The DeLone and McLean model provides the strongest theoretical foundation for this hypothesis because AIS quality can be evaluated through system quality, information quality, service quality, user satisfaction, system use, and net benefits (DeLone & McLean, 1992, 2003).

Prior research supports the importance of AIS quality for financial reporting. Arfismanda et al. (2021) find that AIS and internal control systems influence financial-report quality. Yusnita et al. (2024) examine information technology, AIS, and internal control in relation to financial reporting quality. Suludin et al. (2022) show that accounting information systems affect the quality of financial reports in the Simeuleu District context. Kasdan (2023) finds that AIS implementation and internal audit influence financial-statement quality, with organizational commitment as a moderating variable. Onaolapo et al. (2024) also examine AIS and financial-reporting quality among quoted service companies in Nigeria. Recent AIS research further shows that emerging technologies such as AI, machine learning, cloud computing, blockchain, and RPA are increasingly central to AIS performance and acceptance, although their reporting value depends on system reliability and integration (Al-Khoury et al., 2025; Alslaibi et al., 2025).

AI and digital accounting research further supports this relationship. Prasetianingrum and Sonjaya (2024) argue that digital accounting and AIS have evolved through technologies such as AI, machine learning, cloud computing, and data analytics. Gshayish and Faik (2023) suggest that AI systems improve accounting information quality and support the sustainability of financial-reporting quality. Hasan (2022) indicates that AI tools can support automated analysis and reporting, while Adeoye et al. (2023) emphasize AI's ability to identify patterns and anomalies in accounting and audit data. Brahmantyo et al. (2023) and Gormantara and Elisabeth (2023) also show that the DeLone and McLean model is useful for evaluating information-system success in reporting-related digital systems.

However, evidence is mixed. AIS quality depends not only on technology adoption but also on human competence, data quality, controls, security, and organizational use. Some AIS studies report that internal control or system components may not always significantly affect reporting quality, suggesting that technology benefits depend on implementation conditions (Arfismanda et al., 2021; Kasdan, 2023). AI-enabled AIS may also increase risks related to cybersecurity, algorithmic opacity, and data-governance failure (Hasan, 2022; Anica-Popa et al., 2024; Odogu, 2024). Therefore, AI adoption may improve AIS quality only when the system is integrated into a strong accounting-control environment.

The hypothesis remains justified in Nigeria because AI-enabled AIS can help organizations move beyond fragmented manual accounting systems toward more integrated, automated, and analytically capable reporting environments. Therefore:

H5: Artificial Intelligence adoption is positively associated with accounting information systems quality.

2.6 AI Adoption Challenges and AI Utilization in Accounting Practices

AI adoption challenges are expected to be negatively associated with AI utilization in accounting practices. These challenges include high implementation costs, limited technical skills, weak technological infrastructure, cybersecurity concerns, poor data quality, regulatory uncertainty, resistance to change, lack of management support, and insufficient professional training. TOE explains this relationship because technological, organizational, and environmental barriers can restrict adoption and sustained use (Tornatzky & Fleischer, 1990; Badghish & Soomro, 2024). TAM also supports the relationship because barriers reduce perceived ease of use and may weaken perceived usefulness (Davis, 1989; Venkatesh et al., 2003).

Prior studies identify several barriers to AI utilization. Hasan (2022) highlights ethical, cybersecurity, regulatory, and professional challenges in AI-based accounting and auditing. Anica-Popa et al. (2024) emphasize that accounting and audit professionals need new competencies to use generative AI effectively and manage its risks. Romana et al. (2023) argue that AI changes accountants' roles and requires professional adaptation, digital knowledge, and flexibility. Okoye et al. (2024) show that SMEs in African contexts face budget constraints, skill gaps, cybersecurity risks, and limited resources. Ahmad and Nasseredine (2019) similarly identify implementation costs, skills capacity, technological infrastructure, change management, and government support as barriers to accounting-related reform in Lebanon.

Empirical and conceptual studies in accounting and digital transformation further support this negative relationship. Al Wael et al. (2023) show that organizational and individual factors influence AI adoption in Kuwait's accounting profession. Anh et al. (2024) demonstrate that technology readiness affects AI adoption in accounting and auditing in Vietnam. Hossain et al. (2024) emphasize organizational readiness as a key condition for AI and big data analytics adoption. Mokoginta et al. (2024) identify challenges in RPA implementation in accounting processes. Dahiyat (2022) also examines challenges of RPA implementation in auditing. These studies suggest that utilization depends on more than awareness of AI benefits.

Nevertheless, some counterarguments exist. Organizations may adopt AI despite challenges when competitive pressure, management commitment, vendor support, cloud-based platforms, or regulatory modernization reduce implementation barriers (Badghish & Soomro, 2024; Tasić et al., 2023). Incremental adoption through existing accounting software may also lower cost and complexity. Moreover, professionals who perceive AI as highly useful may continue using it even when implementation is difficult (Davis, 1989; Anh et al., 2024). These arguments suggest that challenges may not completely prevent AI utilization, but they are still likely to reduce the intensity, quality, and sustainability of use.

In Nigeria, AI adoption challenges are particularly important because accounting professionals may face limited training, uneven digital infrastructure, cybersecurity exposure, and resource constraints. These barriers can restrict how frequently and effectively AI is used in accounting practices. Therefore:

H6: AI adoption challenges are negatively associated with AI utilization in accounting practices.

3. Methodology

3.1 Research Design

This study employed a quantitative cross-sectional survey design to examine the association between Artificial Intelligence adoption and perceived financial reporting accuracy among accounting professionals. A quantitative design was appropriate because the study measures respondents' perceptions using structured items and tests statistically specified relationships among AI adoption, organizational readiness, AIS quality, AI adoption challenges, AI utilization, and perceived reporting outcomes. This design is consistent with recent survey-based AI-perception research that uses structured questionnaire data to examine how AI use relates to perceived user understanding, empathy, trust, and cultural alignment in a context-specific setting (Andonia, 2026).

3.2 Study Context and Population

The empirical context of the study is Nigeria. The target population comprised accounting professionals working in accounting, auditing, finance, financial reporting, accounting information systems, and related functions. These respondents included accountants, auditors, financial analysts, finance managers, chief financial officers, accounting consultants, and other professionals involved in preparing, processing, reviewing, analyzing, or using financial information. Their professional roles made them suitable respondents for evaluating how AI-enabled accounting technologies are perceived to relate to financial reporting accuracy, error reduction, timeliness, efficiency, AIS quality, and AI utilization.

3.3 Sampling Strategy and Sample Size

The study used purposive sampling supported by convenience access. Purposive sampling was appropriate because the study required respondents with relevant knowledge of accounting practices, financial reporting, accounting information systems, and AI-enabled technologies. Respondents were therefore selected based on their professional involvement in accounting, auditing, finance, or financial reporting functions. Convenience access was used to facilitate data collection from qualified respondents who were available, accessible, and willing to participate. Although this approach is practical for survey-based accounting research, it limits the extent to which the findings can be generalized beyond the sampled professionals.

The final random sample consisted of 384 accounting professionals. This sample size was considered adequate for descriptive analysis, reliability testing, validity assessment, Pearson correlation analysis, and regression analysis. The sample is also comparable to recent survey-based studies that use professional or domain-specific respondents with an infinite sampling to examine AI perceptions, financial reporting quality, accounting culture, and governance mechanisms (Andonia, 2026; Alslaibi et al., 2025; Hasan Samara et al., 2025).

3.4 Research Instrument and Measurement of Variables

The research instrument was a structured questionnaire divided into two main sections. The first section collected demographic and professional information, including gender, age group, educational qualification, professional experience, job position, area of specialization, organization type, region of work in Nigeria, industry sector, and level of experience with AI-supported accounting tools. These items were used to describe the profile of respondents and assess whether the sample consisted of professionals with relevant accounting and financial reporting experience.

The second section measured the main study constructs: Artificial Intelligence Adoption, Perceived Financial Reporting Accuracy, Perceived Error Reduction, Perceived Timeliness and Efficiency, Organizational Readiness, Accounting Information Systems Quality, AI Adoption Challenges, and AI Utilization in Accounting Practices. All construct items were measured using a five-point Likert scale, where higher scores indicated stronger agreement with the statement and a higher perceived level of the measured construct. The questionnaire items are presented in Annex I. Because the dependent variable is perception-based, the study consistently refers to perceived financial reporting accuracy rather than objectively verified reporting accuracy.

3.5 Validity and Reliability Assessment

Reliability was assessed using Cronbach's alpha. A Cronbach's alpha value of 0.70 or higher was considered acceptable, indicating adequate internal consistency among items measuring the same construct. Construct validity was assessed using the Kaiser-Meyer-Olkin measure, Bartlett's Test of Sphericity, factor loadings, Average Variance Extracted, and Composite Reliability. These procedures were used to evaluate whether the questionnaire items adequately represented the underlying constructs before correlation and regression analyses were conducted.

Because all variables were measured through self-reported questionnaire responses, the study recognizes the possibility of common method bias and social desirability bias. The interpretation of the findings is therefore limited to perceived relationships among constructs. Future versions of the study should include a dedicated common method bias diagnostic, such as Harman's single-factor test, a marker-variable approach, or full collinearity assessment, if the necessary item-level data are available.

3.6 Data Analysis and Model Specification

The collected data were analyzed using descriptive and inferential statistical techniques. Descriptive statistics summarized the demographic and professional characteristics of respondents and the distribution of responses for the main variables. Reliability and validity analyses assessed measurement quality. Pearson correlation analysis examined the direction and strength of associations among the study variables. Regression analysis was then used to test the study hypotheses at the 5% significance level.

The following hypothesis-specific regression models were used:

Model 1: $PFRA_i = \beta_0 + \beta_1 AIA_i + \varepsilon_i$

Model 2: $PER_i = \beta_0 + \beta_1 AIA_i + \varepsilon_i$

Model 3: $PTE_i = \beta_0 + \beta_1 AIA_i + \varepsilon_i$

Model 4: $AIU_i = \beta_0 + \beta_1 OR_i + \varepsilon_i$

Model 5: $AISQ_i = \beta_0 + \beta_1 AIA_i + \varepsilon_i$

Model 6: $AIU_i = \beta_0 + \beta_1 AIC_i + \varepsilon_i$

Where PFRA represents Perceived Financial Reporting Accuracy, AIA represents Artificial Intelligence Adoption, PER represents Perceived Error Reduction, PTE represents Perceived Timeliness and Efficiency, OR represents Organizational Readiness, AISQ represents Accounting Information Systems Quality, AIC represents AI Adoption Challenges, AIU represents AI Utilization in Accounting Practices, β_0 represents the constant term, β_1 represents the regression coefficient, and ε_i represents the error term.

In addition, the following multiple regression model was used to examine the combined association of the key predictors with perceived financial reporting accuracy:

$$PFRA_i = \beta_0 + \beta_1 AIA_i + \beta_2 OR_i + \beta_3 AISQ_i + \beta_4 AIC_i + \varepsilon_i$$

This model assessed whether AI adoption remained significantly associated with perceived financial reporting accuracy after accounting for organizational readiness, accounting information systems quality, and AI adoption challenges. The variance inflation factor values reported in the regression results were used to assess potential multicollinearity among predictors.

3.7 Ethical Considerations and Methodological Boundaries

The questionnaire was used for academic research purposes and did not require respondents to provide personally identifying information. Participation was based on professional judgment and the responses were analyzed in aggregate form. The study also recognizes several methodological boundaries. First, the cross-sectional design does not permit causal inference. Second, the dependent variable measures perceived financial reporting accuracy rather than actual reporting quality. Third, purposive sampling supported by convenience access limits generalizability. Fourth, self-reported data may be affected by common method bias. These limitations are considered when interpreting the findings.

4. Results

This section presents the results of the study on Artificial Intelligence adoption and perceived financial reporting accuracy among accounting professionals in Nigeria. The analysis is based on responses from 384 accounting professionals working in accounting, auditing, finance, financial reporting, accounting information systems, and related functions. The data were analyzed using descriptive statistics, reliability analysis, validity assessment, Pearson correlation analysis, and regression analysis. The hypotheses were tested at the 5% significance level. A hypothesis was considered supported when the coefficient direction was consistent with the expected relationship and the p-value was less than 0.05.

Because the study relies on questionnaire responses, the results should be interpreted as evidence of perceived financial reporting accuracy, not objectively verified reporting accuracy. Therefore, the findings reflect how Nigerian accounting professionals perceive the role of AI adoption in improving reporting accuracy, reducing errors, enhancing timeliness and efficiency, strengthening accounting information systems quality, and supporting AI utilization.

TABLE 1. Demographic Characteristics of Respondents

Variable	**Category**	**Frequency**	**Percentage**
Gender	Male	217	56.5%
	Female	158	41.1%
	Prefer not to say / Other	9	2.4%
Age group	18–24 years	34	8.9%

Variable	Category	Frequency	Percentage
	25–34 years	145	37.8%
	35–44 years	126	32.8%
	45–54 years	62	16.1%
	55 years and above	17	4.4%
Highest educational qualification	Diploma	23	6.0%
	Bachelor's degree	189	49.2%
	Master's degree	119	31.0%
	PhD/Doctorate	18	4.7%
	Professional certification	35	9.1%
Professional experience	Less than 1 year	18	4.7%
	1–3 years	69	18.0%
	4–6 years	111	28.9%
	7–10 years	94	24.5%
	More than 10 years	92	24.0%

Table 1 shows that the sample consisted mainly of male respondents, representing 56.5% of the total sample, while female respondents represented 41.1%. Most respondents were between 25 and 44 years old, indicating that the sample was dominated by professionals in active working-age groups. In terms of education, 49.2% of respondents held a bachelor's degree, while 31.0% held a master's degree. This suggests that the respondents had sufficient academic background to provide informed responses on AI adoption and financial reporting. In addition, 77.4% of respondents had at least four years of professional experience, indicating that the sample included professionals with practical exposure to accounting and financial reporting processes.

TABLE 2. Professional Profile of Respondents

Variable	Category	Frequency	Percentage
Current job position	Accountant	118	30.7%
	Auditor	83	21.6%
	Financial analyst	57	14.8%
	Finance manager	72	18.8%
	Chief financial officer	21	5.5%
	Accounting consultant	33	8.6%
Main area of specialization	Financial reporting	96	25.0%
	Auditing	71	18.5%
	Accounting information systems	63	16.4%
	Taxation	43	11.2%
	Management accounting	49	12.8%
	Financial analysis	39	10.2%
	Risk/internal control	23	6.0%
Type of organization	Private company	125	32.6%
	Public/listed company	74	19.3%
	Audit firm	68	17.7%
	Government/public sector	49	12.8%
	NGO/non-profit	23	6.0%

Variable	Category	Frequency	Percentage
	Educational institution	21	5.5%
	Other	24	6.3%

Table 2 shows that the sample included respondents from different accounting-related roles. Accountants represented the largest group at 30.7%, followed by auditors at 21.6% and finance managers at 18.8%. This distribution is appropriate because the study focuses on accounting professionals who are involved in preparing, reviewing, analyzing, or using financial information. The largest area of specialization was financial reporting, followed by auditing and accounting information systems. This confirms that the sample was relevant to the study's purpose. Respondents also came from different organizational types, with private companies, listed companies, audit firms, and public-sector organizations forming the majority of the sample.

TABLE 3. Nigerian Regional and AI Experience Profile

Variable	Category	Frequency	Percentage
Region of work in Nigeria	Lagos	121	31.5%
	Abuja/FCT	62	16.1%
	South-West excluding Lagos	64	16.7%
	South-East	45	11.7%
	South-South	48	12.5%
	North-West	19	4.9%
	North-Central excluding Abuja	16	4.2%
	North-East	9	2.3%
Industry sector	Banking/financial services	92	24.0%
	Manufacturing	61	15.9%

Variable	Category	Frequency	Percentage
	Retail/wholesale	41	10.7%
	Technology/telecommunications	53	13.8%
	Services	58	15.1%
	Education	26	6.8%
	Public sector	38	9.9%
	Other	15	3.9%
Level of experience with AI-supported accounting tools	No experience	34	8.9%
	Limited awareness only	72	18.8%
	Occasional use	109	28.4%
	Regular use	125	32.6%
	Advanced/professional use	44	11.5%

Table 3 presents the Nigerian contextual profile of the respondents. The largest proportion of respondents worked in Lagos, representing 31.5% of the sample, followed by Abuja/FCT at 16.1%. This is reasonable given the concentration of corporate headquarters, audit firms, financial institutions, and technology-driven organizations in Lagos and Abuja. Respondents were drawn from several sectors, with banking and financial services representing the largest group at 24.0%. This is appropriate because the financial sector in Nigeria is relatively more exposed to digital transformation and AI-enabled accounting tools. Regarding AI experience, 32.6% of respondents reported regular use of AI-supported accounting tools, while 28.4% reported occasional use. This suggests that most respondents had at least some exposure to AI-enabled accounting systems.

TABLE 4. Reliability Statistics

Construct	Code	Number of Items	Cronbach's Alpha
Artificial Intelligence Adoption	AIA	7	0.889
Perceived Financial Reporting Accuracy	PFRA	6	0.904
Perceived Error Reduction	PER	6	0.872
Perceived Timeliness and Efficiency	PTE	6	0.886
Organizational Readiness	OR	7	0.891
Accounting Information Systems Quality	AISQ	7	0.906
AI Adoption Challenges	AIC	7	0.858
AI Utilization in Accounting Practices	AIU	7	0.881

Table 4 presents the reliability results for the study constructs. Cronbach's alpha values ranged from 0.858 to 0.906, which indicates strong internal consistency across all constructs. The highest reliability value was recorded for Accounting Information Systems Quality at 0.906, followed by Perceived Financial Reporting Accuracy at 0.904. Since all Cronbach's alpha values exceeded the minimum acceptable threshold of 0.70, the measurement items were considered reliable for further analysis.

TABLE 5. KMO and Bartlett's Test

Test	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.912
Bartlett's Test of Sphericity Approx. Chi-square	11863.420
Degrees of freedom	1128

Test	Value
Significance	<0.001

Table 5 presents the validity assessment using the Kaiser-Meyer-Olkin measure and Bartlett's Test of Sphericity. The KMO value was 0.912, indicating that the sample was adequate for factor analysis. Bartlett's Test of Sphericity was statistically significant at $p < 0.001$, suggesting that the correlation matrix was suitable for identifying underlying constructs. These results support the construct validity of the questionnaire.

TABLE 6. Construct Validity Summary

Construct	Factor Loading Range	AVE	Composite Reliability	Validity Decision
Artificial Intelligence Adoption	0.681–0.842	0.584	0.907	Valid
Perceived Financial Reporting Accuracy	0.702–0.864	0.611	0.918	Valid
Perceived Error Reduction	0.674–0.831	0.562	0.895	Valid
Perceived Timeliness and Efficiency	0.689–0.846	0.579	0.902	Valid
Organizational Readiness	0.695–0.851	0.588	0.909	Valid
Accounting Information Systems Quality	0.713–0.872	0.619	0.920	Valid
AI Adoption Challenges	0.661–0.816	0.544	0.887	Valid
AI Utilization in Accounting Practices	0.682–0.840	0.571	0.899	Valid

Table 6 shows that all factor loadings exceeded 0.60, indicating that the questionnaire items loaded adequately on their respective constructs. The Average Variance Extracted values were above 0.50 for all constructs, while composite reliability values were above 0.80. These results indicate acceptable convergent validity and support the use of the constructs in correlation and regression analysis.

TABLE 7. Descriptive Statistics

Construct	N	Minimum	Maximum	Mean	Standard Deviation	Interpretation
Artificial Intelligence Adoption	384	1.71	5.00	3.78	0.72	High
Perceived Financial Reporting Accuracy	384	1.83	5.00	3.91	0.68	High
Perceived Error Reduction	384	1.67	5.00	3.87	0.70	High
Perceived Timeliness and Efficiency	384	1.67	5.00	3.84	0.73	High
Organizational Readiness	384	1.57	5.00	3.69	0.76	High
Accounting Information Systems Quality	384	1.71	5.00	3.88	0.69	High
AI Adoption Challenges	384	1.43	5.00	3.54	0.81	Moderate to high
AI Utilization in Accounting Practices	384	1.57	5.00	3.61	0.78	Moderate to high

Table 7 presents the descriptive statistics for the study variables. The mean score for Artificial Intelligence Adoption was 3.78, suggesting that respondents generally agreed that AI-supported tools are being used in accounting and financial reporting functions in Nigeria. Perceived Financial Reporting Accuracy had the highest mean score of 3.91, indicating that respondents generally perceived AI-supported systems as improving the reliability, completeness, and accuracy of financial reporting.

Accounting Information Systems Quality also had a high mean score of 3.88, suggesting that respondents perceived their accounting systems as reliable and useful for financial reporting. AI Adoption Challenges had a mean score of 3.54, indicating that respondents recognized the presence of implementation barriers, including cost, technical skill limitations, cybersecurity concerns, and resistance to change.

TABLE 8. Pearson Correlation Matrix

Variable	**AIA**	**PFRA**	**PER**	**PTE**	**OR**	**AISQ**	**AIC**	**AIU**
AIA	1.000							
PFRA	0.641***	1.000						
PER	0.598***	0.609***	1.000					
PTE	0.574***	0.592***	0.621***	1.000				
OR	0.482***	0.475***	0.408***	0.402***	1.000			
AISQ	0.612***	0.651***	0.552***	0.527***	0.558***	1.000		
AIC	-0.291***	-0.243***	-0.218***	-0.196***	-0.352***	-0.267***	1.000	
AIU	0.548***	0.506***	0.491***	0.513***	0.467***	0.522***	-0.413***	1.000

Note: *** $p < 0.001$.

AIA = Artificial Intelligence Adoption; PFRA = Perceived Financial Reporting Accuracy; PER = Perceived Error Reduction; PTE = Perceived Timeliness and Efficiency; OR = Organizational Readiness; AISQ = Accounting Information Systems Quality; AIC = AI Adoption Challenges; AIU = AI Utilization.

Table 8 shows the correlation results among the study variables. Artificial Intelligence Adoption was positively and significantly correlated with Perceived Financial Reporting Accuracy ($r = 0.641$, $p < 0.001$), Perceived Error Reduction ($r = 0.598$, $p < 0.001$), Perceived Timeliness and Efficiency ($r = 0.574$, $p < 0.001$), Accounting Information Systems Quality ($r = 0.612$, $p < 0.001$), and AI Utilization ($r = 0.548$, $p < 0.001$). These results suggest that higher AI adoption is associated with stronger perceived improvements in reporting accuracy, error reduction, efficiency, AIS quality, and utilization.

Organizational Readiness was also positively correlated with AI Utilization ($r = 0.467$, $p < 0.001$), indicating that organizations with stronger infrastructure, management support, training, and resources are more likely to report higher use of AI in accounting practices. AI Adoption Challenges were negatively correlated with AI Utilization ($r = -0.413$, $p < 0.001$), suggesting that implementation barriers are associated with lower effective use of AI in accounting functions.

TABLE 9. Model Summary for Perceived Financial Reporting Accuracy

Model	**R**	**R^2**	**Adjusted R^2**	**Std. Error of Estimate**	**Durbin-Watson**
1	0.729	0.532	0.527	0.467	1.891

Table 9 shows that the model explained 53.2% of the variance in perceived financial reporting accuracy. The adjusted R^2 value of 0.527 indicates that AI adoption, organizational readiness, accounting information systems quality, and AI adoption challenges jointly explain a substantial proportion of the variation in perceived financial reporting accuracy among Nigerian accounting professionals. The Durbin-Watson value of 1.891 is close to 2.0, suggesting no serious autocorrelation concern.

TABLE 10. ANOVA for Main Regression Model

Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Regression	93.815	4	23.454	107.600	<0.001
Residual	82.622	379	0.218		
Total	176.437	383			

Table 10 shows that the main regression model was statistically significant, $F(4, 379) = 107.600$, $p < 0.001$. This indicates that the combined predictors significantly explain perceived financial reporting accuracy.

TABLE 11. Multiple Regression Coefficients for Perceived Financial Reporting Accuracy

Predictor	**B**	**Std. Error**	**Beta**	**t**	**Sig.**	**VIF**
Constant	0.831	0.177	—	4.695	<0.001	—
Artificial Intelligence Adoption	0.386	0.049	0.411	7.878	<0.001	1.914
Organizational Readiness	0.126	0.041	0.141	3.073	0.002	1.621
Accounting Information Systems Quality	0.318	0.052	0.322	6.115	<0.001	1.872
AI Adoption Challenges	-0.057	0.032	-0.068	-1.773	0.077	1.193

Table 11 shows that Artificial Intelligence Adoption was positively and statistically associated with Perceived Financial Reporting Accuracy ($\beta = 0.411$, $p < 0.001$). This means that higher AI adoption is associated with higher perceived reporting accuracy among Nigerian accounting professionals. Accounting Information Systems Quality was also positively and significantly associated with PFRA ($\beta = 0.322$, $p < 0.001$), suggesting that reliable and integrated AIS is linked to stronger perceptions of financial reporting accuracy. Organizational Readiness was also significant ($\beta = 0.141$, $p = 0.002$), indicating that management support, infrastructure, training, and resources are associated with better perceived reporting outcomes. AI Adoption Challenges had a negative but non-significant association in the main model ($\beta = -0.068$, $p = 0.077$), suggesting that challenges may be linked to lower perceived reporting accuracy, but their direct association becomes weaker when AI adoption, organizational readiness, and AIS quality are included in the same model.

TABLE 12. Regression Model Results for H1–H6

Hypothesis	**Model**	**R**	**R^2**	**Adjusted R^2**	**F**	**Sig.**
H1	AIA → PFRA	0.641	0.411	0.409	266.016	<0.001
H2	AIA → PER	0.598	0.358	0.356	213.744	<0.001
H3	AIA → PTE	0.574	0.329	0.327	187.690	<0.001
H4	OR → AIU	0.467	0.218	0.216	106.296	<0.001

Hypothesis	Model	R	R^2	Adjusted R^2	F	Sig.
H5	AIA → AISQ	0.612	0.374	0.373	228.301	<0.001
H6	AIC → AIU	0.413	0.171	0.169	78.501	<0.001

Note: H4 was tested using AI utilization in accounting practices because the revised hypothesis focuses on the association between organizational readiness and AI utilization.

Table 12 shows that all six hypothesis-specific regression models were statistically significant at $p < 0.001$. AI adoption explained 41.1% of the variance in perceived financial reporting accuracy, 35.8% of the variance in perceived error reduction, 32.9% of the variance in perceived timeliness and efficiency, and 37.4% of the variance in accounting information systems quality. Organizational readiness explained 21.8% of the variance in AI utilization, while AI adoption challenges explained 17.1% of the variance in AI utilization.

TABLE 13. Hypothesis-Specific Regression Coefficients

Hypothesis	Relationship	B	Std. Error	Beta	t	Sig.	Direction
H1	AIA → PFRA	0.607	0.037	0.641	16.310	<0.001	Positive
H2	AIA → PER	0.584	0.040	0.598	14.620	<0.001	Positive
H3	AIA → PTE	0.582	0.042	0.574	13.700	<0.001	Positive
H4	OR → AIU	0.478	0.046	0.467	10.310	<0.001	Positive
H5	AIA → AISQ	0.586	0.039	0.612	15.110	<0.001	Positive
H6	AIC → AIU	-0.397	0.045	-0.413	-8.860	<0.001	Negative

Table 13 presents the coefficients for the hypothesis-specific regression tests. H1 was supported because AI adoption was positively and significantly associated with perceived financial reporting accuracy ($\beta = 0.641$, $p < 0.001$). H2 was supported because AI adoption was positively and significantly associated with perceived error reduction ($\beta = 0.598$, $p < 0.001$). H3 was supported because AI adoption was positively and significantly associated with perceived timeliness and efficiency ($\beta = 0.574$, $p < 0.001$). H4 was supported because organizational readiness was positively associated with AI utilization ($\beta = 0.467$, $p < 0.001$). H5 was supported because AI adoption was positively and significantly associated with AIS quality ($\beta = 0.612$, $p < 0.001$). H6 was also supported because AI adoption challenges were negatively and significantly associated with AI utilization ($\beta = -0.413$, $p < 0.001$).

5. Discussion

The findings provide evidence that AI adoption is positively associated with perceived financial reporting accuracy among accounting professionals in Nigeria. This result suggests that professionals who report higher use of AI-supported accounting tools also tend to perceive financial reporting as more accurate, reliable, complete, and useful. The finding is consistent with prior studies showing that advanced digital technologies, including AI, big data analytics, machine learning, and intelligent accounting systems, can support reporting processes by improving data processing, anomaly detection, reporting consistency, and analytical capacity (Saleh et al., 2022; Younis, 2020; Hung et al., 2023; Gshayish & Faik, 2023). It also aligns with TAM, because AI appears to be valued when professionals perceive it as useful for improving reporting-related tasks, and with the DeLone and McLean model, because AI-supported systems may strengthen perceived information quality, system reliability, and decision usefulness (Davis, 1989; DeLone & McLean, 1992, 2003).

The positive associations between AI adoption, perceived error reduction, and reporting timeliness and efficiency indicate that accounting professionals view AI as useful for reducing manual processing limitations. AI-supported systems may help automate repetitive procedures, validate accounting data, flag unusual transactions, support reconciliations, and accelerate access to financial information. These findings are consistent with studies on robotic process automation and audit data analytics, which suggest that automation improves accounting and auditing processes by reducing repetitive manual work, detecting unusual transactions, and supporting more efficient analysis (Tiron-Tudor et al., 2024; Mokoginta et al., 2024; Dahiyat, 2022; Ditkaew & Suttipun, 2023). They also support the view that data analytics can help accountants and auditors improve risk assessment, exception reporting, and reporting-related analysis (Chu & Yong, 2021; Balios et al., 2020).

Organizational readiness was positively associated with AI utilization, supporting the TOE-based argument that AI implementation depends not only on the availability of AI tools but also on infrastructure, management support, employee training, financial resources, data quality, and cybersecurity readiness. This interpretation is also consistent with Behavioral-Governance Fit Theory, because AI tools are more likely to be used effectively when technological capability, governance arrangements, and professional routines fit together rather than operate as disconnected elements (Alslaibi et al., 2026). The result further aligns with emerging-market evidence showing that AI can complement corporate governance mechanisms when organizational structures support digital adoption (Amarna et al., 2025). Therefore, AI adoption should not be treated as a purely technological decision; it is also an organizational capability and governance-fit issue.

The positive relationship between AI adoption and accounting information systems quality further suggests that AI may contribute to perceived reporting accuracy through the underlying quality of AIS. AI-supported accounting systems can improve data integration, accessibility, validation, automation, and analytical functionality. This supports the DeLone and McLean perspective that system quality and information quality are central to information-system success. It is also consistent with recent evidence that AI can strengthen financial statement transparency when AIS reliability is high, and that emerging technologies are increasingly embedded in AIS research streams (Al-Khoury et al., 2025; Alslaibi et al., 2025). In practical terms, AI may not improve reporting perceptions independently; rather, its perceived value is likely to depend on whether it is embedded in reliable, well-integrated, and well-governed accounting information systems.

The findings also show that AI adoption challenges are negatively associated with AI utilization. This means that implementation costs, technical skill limitations, cybersecurity concerns, resistance to change, poor data quality, and infrastructure weaknesses may restrict the effective use of AI in accounting practices. This result is consistent with prior research identifying technical, ethical, organizational, and regulatory barriers as major constraints on AI adoption in accounting and auditing (Hasan, 2022; Anica-Popa et al., 2024; Okoye et al., 2024; Romana et al., 2023). However, AI adoption challenges were negative but not statistically significant in the multiple regression model predicting perceived financial reporting accuracy. This suggests that the direct association between challenges and perceived reporting accuracy may weaken once AI adoption, organizational readiness, and AIS quality are considered. A plausible interpretation is that implementation barriers reduce AI utilization, but their relationship with perceived reporting accuracy may be indirect and conditional on the strength of organizational readiness and AIS quality.

Overall, the study contributes to the literature by showing that AI adoption is perceived by Nigerian accounting professionals as beneficial for reporting accuracy, error reduction, timeliness, efficiency, AIS quality, and AI utilization. Nevertheless, the findings should be interpreted cautiously. The study does not demonstrate that AI adoption objectively reduces reporting errors, restatements, audit adjustments, or reporting delays. Instead, it shows that professionals perceive AI-supported systems as improving reporting-related processes. Future research should therefore combine survey-based perceptions with objective reporting-quality indicators.

6. Conclusion and Implications

This study examined the association between Artificial Intelligence adoption and perceived financial reporting accuracy among accounting professionals in Nigeria. The findings indicate that AI adoption is positively associated with perceived financial reporting accuracy, perceived error reduction, perceived timeliness and efficiency, and accounting information systems quality. Organizational readiness was positively associated with AI utilization, while AI adoption challenges were negatively associated with AI utilization. In the main regression model, AI adoption, organizational readiness, and accounting information systems quality significantly predicted perceived financial reporting accuracy, whereas AI adoption challenges had a negative but statistically weaker association when the other predictors were included.

The study contributes theoretically by integrating the Technology Acceptance Model, the Technology-Organization-Environment framework, the DeLone and McLean Information Systems Success Model, and Behavioral-Governance Fit Theory to explain how AI adoption relates to perceived reporting outcomes. TAM helps explain why accounting professionals may value AI when it is perceived as useful for improving reporting tasks. TOE explains why organizational readiness and implementation barriers shape AI utilization. DeLone and McLean's model explains why AIS quality is central to the perceived usefulness of AI-supported reporting systems. BGFT extends the framework by emphasizing that AI-related reporting benefits depend on the fit between technological tools, governance safeguards, organizational routines, and professional behavior.

The study also offers practical implications for organizations and accounting professionals. Organizations seeking to adopt AI in accounting should not focus only on acquiring AI tools; they should also invest in digital infrastructure, employee training, data quality, cybersecurity controls, management support, and system integration. Accounting professionals should develop digital competence and maintain professional skepticism when interpreting AI-generated outputs. AI should support, rather than replace, professional judgment in financial reporting.

For regulators and professional accounting bodies, the findings suggest the need for clearer guidance on responsible AI use in accounting and reporting. Training programs, ethical standards, cybersecurity guidance, and governance frameworks are needed to ensure that AI adoption supports reporting reliability without creating new risks related to algorithmic opacity, data quality, or overreliance on automation.

7. Limitations and Future Research

The study has several limitations. First, the cross-sectional design prevents causal inference. Second, the study measures perceived financial reporting accuracy rather than objective reporting quality. Third, the use of purposive sampling supported by convenience access limits generalizability. Fourth, self-reported data may be affected by common method bias and social desirability bias. Finally, the study is limited to Nigerian accounting professionals, so the findings should not be generalized to all emerging economies without further evidence.

Future research should use longitudinal designs and objective reporting-quality indicators such as audit adjustments, financial restatements, reporting delays, internal control weaknesses, discretionary accruals, or actual error rates. Comparative studies across different emerging economies would also help determine whether institutional, regulatory, and technological conditions shape the effectiveness of AI adoption in accounting. Qualitative studies involving accountants, auditors, finance managers, and regulators could further explain how AI is implemented, trusted, governed, and used in real financial reporting environments.

Declarations

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Conflict of Interest

The authors declare that they have no competing interests.

Ethics Approval

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki. The study involved voluntary survey participation by adult respondents. According to the applicable institutional requirements, formal ethical approval was not required for this type of non-interventional questionnaire-based research.

Consent to Participate

Informed consent was obtained from all participants prior to their participation in the study.

Consent for Publication

Not applicable.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Authors' Contributions

F contributed to the structure draft writing, while M contributed in the Analysis.

Clinical Trial Number

Not applicable.

Use of Artificial Intelligence

The authors declare that generative artificial intelligence (AI) tools were used only to assist with language editing and clarity of expression during the preparation of the manuscript. The authors reviewed and edited all AI-assisted outputs and take full responsibility for the content, interpretation, and conclusions of the manuscript. No AI tools were used to generate, manipulate, or analyze the research data or to produce the scientific results of the study.

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Annex I

Questionnaire

Artificial Intelligence Adoption and Perceived Financial Reporting Accuracy: Evidence from Accounting Professionals in Nigeria

Purpose: This questionnaire collects responses from accounting professionals in Nigeria regarding Artificial Intelligence adoption, perceived financial reporting accuracy, organizational readiness, accounting information systems quality, and AI adoption challenges.

Instructions: Please answer all questions based on your professional experience. For Section B, indicate your level of agreement with each statement using the scale provided. Your responses will be used for academic research purposes only and will be treated confidentially.

Likert Scale for Section B: 1 = Strongly Disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Strongly Agree.

Section A: Demographic and Professional Information

Please tick or mark the option that best describes you.

Code	Question	Response Options
D1	Gender	[ ] Male [ ] Female [ ] Prefer not to say [ ] Other: __________
D2	Age group	[ ] 18-24 [ ] 25-34 [ ] 35-44 [ ] 45-54 [ ] 55 and above
D3	Highest educational qualification	[ ] Diploma [ ] Bachelor degree [ ] Master degree [ ] PhD/Doctorate [ ] Professional certification [ ] Other: __________
D4	Professional experience in accounting/finance	[ ] Less than 1 year [ ] 1-3 years [ ] 4-6 years [ ] 7-10 years [ ] More than 10 years
D5	Current job position	[ ] Accountant [ ] Auditor [ ] Financial analyst [ ] Finance manager [ ] Chief financial officer [ ] Accounting consultant [ ] Other: __________
D6	Main area of specialization	[ ] Financial reporting [ ] Auditing [ ] Accounting information systems [ ] Taxation [ ] Management accounting [ ] Financial analysis [ ] Risk/internal control [ ] Other: __________

D7	Type of organization	[ ] Private company [ ] Public/listed company [ ] Audit firm [ ] Government/public sector [ ] NGO/non-profit [ ] Educational institution [ ] Other: __________
D8	Industry sector	[ ] Banking/financial services [ ] Manufacturing [ ] Retail/wholesale [ ] Technology/telecommunications [ ] Services [ ] Education [ ] Public sector [ ] Other: __________
D9	Country or region of work	[ ] ______________________________
D10	Level of experience with AI-supported accounting tools	[ ] No experience [ ] Limited awareness only [ ] Occasional use [ ] Regular use [ ] Advanced/professional use

Section B: Study Constructs

Please mark one response for each statement.

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

Section B1: Artificial Intelligence Adoption

Code	Questionnaire Statement	1	2	3	4	5
AIA1	My organization uses Artificial Intelligence tools in accounting and financial reporting activities.	[]	[]	[]	[]	[]
AIA2	My organization uses machine learning applications to support accounting processes.	[]	[]	[]	[]	[]
AIA3	Robotic Process Automation is used to automate routine accounting tasks.	[]	[]	[]	[]	[]
AIA4	Predictive analytics tools are used to support financial forecasting and decision-making.	[]	[]	[]	[]	[]
AIA5	Intelligent accounting systems are used to process and analyze accounting data.	[]	[]	[]	[]	[]
AIA6	Automated reporting tools are used to support the preparation of financial reports.	[]	[]	[]	[]	[]
AIA7	AI-supported data analysis is used to improve accounting and reporting activities.	[]	[]	[]	[]	[]

Section B2: Perceived Financial Reporting Accuracy

Code	Questionnaire Statement	1	2	3	4	5
PFRA1	Financial reports prepared using AI-supported systems are perceived as accurate.	[ ]	[ ]	[ ]	[ ]	[ ]
PFRA2	AI-supported accounting systems improve the reliability of financial information.	[ ]	[ ]	[ ]	[ ]	[ ]
PFRA3	AI adoption improves the completeness of financial reporting information.	[ ]	[ ]	[ ]	[ ]	[ ]
PFRA4	AI-supported systems help ensure compliance with accounting standards.	[ ]	[ ]	[ ]	[ ]	[ ]
PFRA5	AI adoption increases confidence in the accuracy of reported financial data.	[ ]	[ ]	[ ]	[ ]	[ ]
PFRA6	AI-supported accounting systems improve the overall quality of financial reporting.	[ ]	[ ]	[ ]	[ ]	[ ]

Section B3: Perceived Error Reduction

Code	Questionnaire Statement	1	2	3	4	5
PER1	AI adoption reduces manual errors in accounting processes.	[ ]	[ ]	[ ]	[ ]	[ ]
PER2	AI-supported systems improve the validation of accounting data.	[ ]	[ ]	[ ]	[ ]	[ ]
PER3	AI adoption reduces processing mistakes in financial reporting.	[ ]	[ ]	[ ]	[ ]	[ ]
PER4	AI tools help detect anomalies or unusual transactions in accounting records.	[ ]	[ ]	[ ]	[ ]	[ ]
PER5	AI adoption improves the consistency of accounting records.	[ ]	[ ]	[ ]	[ ]	[ ]

PER6	AI-supported systems reduce the likelihood of financial reporting errors.	[]	[]	[]	[]	[]

Section B4: Perceived Timeliness and Efficiency

Code	Questionnaire Statement	1	2	3	4	5
PTE1	AI adoption speeds up the preparation of financial reports.	[]	[]	[]	[]	[]
PTE2	AI-supported systems reduce the time required to process accounting information.	[]	[]	[]	[]	[]
PTE3	AI adoption improves workflow efficiency in financial reporting processes.	[]	[]	[]	[]	[]
PTE4	AI-supported systems provide faster access to financial information.	[]	[]	[]	[]	[]
PTE5	AI adoption supports more timely financial analysis.	[]	[]	[]	[]	[]
PTE6	AI tools improve the overall efficiency of financial reporting activities.	[]	[]	[]	[]	[]

Section B5: Organizational Readiness

Code	Questionnaire Statement	1	2	3	4	5
OR1	My organization has adequate technological infrastructure to implement AI in accounting functions.	[]	[]	[]	[]	[]
OR2	Top management supports the adoption of AI technologies in accounting.	[]	[]	[]	[]	[]
OR3	Employees receive sufficient training to use AI-supported accounting systems.	[]	[]	[]	[]	[]
OR4	My organization has sufficient financial resources to implement AI technologies.	[]	[]	[]	[]	[]
OR5	My organization has reliable data systems that support AI implementation.	[]	[]	[]	[]	[]

OR6	My organization is willing to adopt AI technologies in accounting and financial reporting.	[]	[]	[]	[]	[]
OR7	My organization has the technical capacity needed to implement AI in accounting functions.	[]	[]	[]	[]	[]

Section B6: Accounting Information Systems Quality

Code	Questionnaire Statement	1	2	3	4	5
AISQ1	The accounting information system used in my organization is reliable.	[]	[]	[]	[]	[]
AISQ2	The accounting information system provides accurate financial information.	[]	[]	[]	[]	[]
AISQ3	The accounting information system integrates data from different accounting functions effectively.	[]	[]	[]	[]	[]
AISQ4	The accounting information system allows easy access to relevant financial information.	[]	[]	[]	[]	[]
AISQ5	The accounting information system supports efficient financial reporting.	[]	[]	[]	[]	[]
AISQ6	The accounting information system provides useful information for accounting decision-making.	[]	[]	[]	[]	[]
AISQ7	The accounting information system supports the preparation of timely financial reports.	[]	[]	[]	[]	[]

Section B7: AI Adoption Challenges

Code	Questionnaire Statement	1	2	3	4	5
AIC1	High implementation cost limits the adoption of AI in accounting practices.	[]	[]	[]	[]	[]
AIC2	Lack of technical skills limits the effective use of AI in accounting functions.	[]	[]	[]	[]	[]

AIC3	Cybersecurity concerns hinder the adoption of AI-supported accounting systems.	[]	[]	[]	[]	[]
AIC4	Resistance to change limits the adoption of AI technologies in accounting.	[]	[]	[]	[]	[]
AIC5	Poor data quality creates challenges for AI adoption in accounting practices.	[]	[]	[]	[]	[]
AIC6	Inadequate technological infrastructure limits AI adoption in accounting.	[]	[]	[]	[]	[]
AIC7	Regulatory uncertainty creates challenges for the use of AI in accounting and financial reporting.	[]	[]	[]	[]	[]

Section B8: AI Utilization in Accounting Practices

Code	Questionnaire Statement	1	2	3	4	5
AIU1	AI tools are used in transaction processing within accounting functions.	[]	[]	[]	[]	[]
AIU2	AI tools are used to support account reconciliation activities.	[]	[]	[]	[]	[]
AIU3	AI tools are used in the preparation of financial reports.	[]	[]	[]	[]	[]
AIU4	AI tools are used to support financial forecasting.	[]	[]	[]	[]	[]
AIU5	AI tools are used to support audit-related activities.	[]	[]	[]	[]	[]
AIU6	AI tools are used to detect anomalies or unusual transactions.	[]	[]	[]	[]	[]
AIU7	AI tools are used to support accounting decision-making.	[]	[]	[]	[]	[]

Thank you for your participation.