

Artificial intelligence adoption and financial reporting quality in financial institutions: the role of data governance, organisational readiness and governance oversight

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Abstract

Purpose: This study investigated the effects of artificial intelligence (AI) adoption on the quality of financial reporting of Nigerian financial institutions, with data governance quality as the mediator and organisational readiness and governance oversight as the moderators.

Methodology: A quantitative, cross-sectional survey yielded 350 valid responses from finance, accounting, audit, compliance, risk, management, information technology and data professionals. Descriptive statistics, reliability and validity tests, correlation analysis and regression-based structural modelling were used to analyze the data.

Results and conclusion: AI adoption was positively associated with financial reporting quality. Data governance quality partly explained this relationship, showing that reliable, traceable and well-controlled data are important to the reporting value of AI. Organisational readiness did not significantly change the relationship between AI adoption and reporting quality. Governance oversight had a significant moderating effect, but its direction was negative rather than positive as proposed. Overall, AI adoption alone was not sufficient to ensure higher reporting quality; its contribution depended on the quality of the data environment and how oversight was exercised.

Implication of findings: Boards and regulators should establish technically sound and risk-based oversight of financial institutions that ensures accountability while fostering responsible innovation, while financial institutions need to integrate AI into data governance, finance, audit and internal-control frameworks.

Keywords: Artificial intelligence adoption; data governance quality; financial reporting quality; organisational readiness; governance oversight

1. Introduction

Financial institutions are increasingly transforming artificial intelligence (AI) into a strategic tool and not just a single operation. In financial services, AI-powered systems are leveraged for robotic process automation, credit analysis, fraud prevention, detecting anomalies, compliance auditing, and customer data analysis and support. In addition to automation, these applications change the way financial data is created, verified and applied in managerial and regulatory decisions. For instance, Fedyk et al. (2022) demonstrated that investment in AI by audit firms is linked to audit-quality benefits like lower audit-restatement risk. This means that AI can impact the quality of the assurance and the reliability of the reports, rather than just the speed of executing the exercise.

Financial reporting quality is important because it supports accountability and informed economic decisions. Investors, lenders and other creditors use financial information to assess an entity's prospects and management's stewardship of its resources (International Accounting Standards Board [IASB], 2018). Poor-quality reporting can therefore weaken stakeholder confidence. In this study, financial reporting quality refers to the extent to which financial information is accurate, timely, complete, transparent, comparable and verifiable. Existing studies also assess reporting quality through attributes such as relevance and faithful representation (Johri, 2024) and through accrual quality, earnings timeliness and accounting conservatism (Lisboa et al., 2025).

The use of AI can enhance the quality of financial reporting as it facilitates the better capture, processing and review of financial information. These systems can help cut down on manual inaccuracies, speed-up reconciliation, detect irregular transactions, and assist with audit and compliance checks. AI adoption has been linked to lower discretionary accruals and better matching of accrual and cash flow in this study by Anantharaman et al., (2023), suggesting higher reporting quality. Similarly, Li (2026) shows that the adoption of AI leads to better disclosure quality due to the clear and accurate presentation of corporate information. The results, however, also indicate that the quality of reporting can only be enhanced by the use of AI where it enhances the processes, rather than being used symbolically.

Nigeria offers a relevant example of an emerging economy to consider the connection, as financial institutions in the country are being exposed to more fintech competition, expanded digital banking adoption and fraud risk. Odufisan et al. (2025) contend that AI tools are critical in combating fraud in today's digital age, where traditional methods fall short in detecting fraud at the pace and complexity of the online environment. Likewise, Alaba et al. (2025) report that factors such as management support, pressure from the infrastructure and regulations limit the adoption of AI in Nigerian banks, while cost and technical expertise remain significant challenges. This context emphasizes the opportunities and challenges for implementing AI.

Therefore, it is a poor reflection to believe that implementing AI leads to financial reporting quality by itself. In emerging economies, financial institutions typically have disjointed systems, inconsistent data governance, and limited AI skills. Kokina et al. (2025) demonstrate that although simple AI tools are extensively applied in auditing, more sophisticated versions are limited by issues of transparency, bias, data privacy, and data reliability. This indicates that AI can enhance the quality of reporting only if there's proper governance and placement within the reporting processes.

While prior research has investigated the role of AI in auditing and reporting, the evidence available to account for the impact of AI on the quality of financial reporting in financial institutions in Africa is limited. Specifically, there has been little focus on data governance and the circumstances in which AI can enhance reporting results. According to Bin-Nashwan et al. (2025), the use of AI can facilitate the accuracy of reporting and decrease information asymmetry, though with the caveat that it relies on adequate data governance. This suggests that there is a relationship between organisational and governance aspects and the effect of AI on reporting quality.

Accordingly, this study examines the relationship between AI adoption and financial reporting quality in financial institutions operating in Nigeria. It tests data governance quality as a mediator and organisational readiness and governance oversight as moderators. By focusing on an emerging economy, the study provides evidence on whether the reporting value of AI depends on an institution's data and governance arrangements.

2. Literature review

Artificial intelligence adoption in financial institutions

AI adoption in financial institutions refers to the integration of technologies such as machine learning, natural language processing (NLP), predictive analytics and automation into financial, operational and control activities. NLP enables computer systems to interpret, analyse and generate human language. AI adoption therefore involves more than acquiring software. It requires institutions to incorporate these tools into routine work, decision-making and internal controls. Bin-Nashwan et al. (2025) found that

competitive pressure, vendor support, management commitment and organisational readiness shape AI adoption in accounting and auditing settings.

In reality, these AI applications include accounting automation, credit scoring, fraud detection, compliance monitoring, and risk assessment and financial reporting support. These are particularly important in high transaction and highly regulated environments. AI investment boosts audit quality and efficiency, which lowers the risk of audits being restated and audit fees, potentially impacting labour demand (Fedyk et al., 2022). AI for fraud detection is being embraced in Nigeria due to the support of management, IT infrastructure, and staff skills, while also being limited by cost and technical issues, according to Alaba et al. (2025). The rate and trajectory of AI's use should be considered a journey of learning, integration, and governance within the organization.

Financial reporting quality

Financial reporting quality is the degree of accuracy, timeliness, completeness and reliability of financial reporting for decision-making purposes. Reporting quality matters in financial institutions because it influences regulatory oversight, capital allocation, risk evaluation, and organisational credibility. Reporting quality can affect confidence and jeopardise institutions' ability to avoid sanctions and reputational risk.

Financial reporting quality is considered multidimensional in the literature. The two attributes emphasized by Johri (2024) are relevance and accuracy, and the two additional attributes mentioned by Lisboa et al. (2025) are accrual quality and accounting conservatism. These dimensions demonstrate the importance of reporting beyond compliance to the usefulness and integrity of the financial information. For example, accuracy can be achieved if it is not timely, or timeliness can be achieved if it is not accurate. Comparability and traceability also help to verify and maintain consistency for periods. Sadiq, O. A., & Dennis, O. A. (2026) expatiated that timely reporting of financial statements has the advantages of improved quality financial reporting and transparency and reliability of accounting information.

Thus, this study utilises a multidimensional approach to financial reporting quality, namely, accuracy, timeliness, completeness, transparency, reliability and comparability, to reflect the impact of AI-enabled processes on financial reporting.

AI adoption and financial reporting quality

AI can help improve financial reporting quality by augmenting the way financial data is generated, processed, and validated. AI systems minimise manual mistakes, automate reconciliation, identify anomalies, assist with accounting estimates and shorten reporting cycles. These features are especially useful in the highly intricate and data-driven financial landscape. Gbenga and Olabisi (2025) observed that AI encompasses tools such as machine learning, predictive analytics, natural language processing, and robotic process automation, all designed to improve efficiency, accuracy, and transparency in data-driven decision-making. This makes their usage in the financial reporting process a panacea for quality output.

This relationship has been verified by empirical evidence. Increased use of AI leads to lower discretionary accruals and better accrual-cash flow matching, suggesting better reporting quality (Anantharaman et al., 2023). According to Li (2026), AI improves disclosure readability and accuracy, both in terms of content and presentation. These results indicate that AI enhances the quality of reporting by facilitating better data processing and disclosure.

The relationship is, however, contingent. Kokina et al. (2025) identify issues of transparency, the ability to explain, and overreliance on AI, particularly when it comes to audits. When the logic in the evidence is not transparent to professionals, they might not trust it, as demonstrated by Commerford et al. (2022). These risks imply that AI can introduce new challenges if outputs are not properly validated. Given this, the impact of AI on financial reporting quality is likely to be positive but contingent on the governance and control mechanisms.

Data governance quality

Data governance quality is the policy, systems and control that make sure that data is accurate, complete, consistent, accessible and auditable. It is vital in AI-integrated settings as AI systems rely on data quality. Inaccurate data may also result in inaccurate forecasts, incorrect results and false reporting.

Bin-Nashwan et al. (2025) show that strong data governance enhances the benefits of AI by improving reporting accuracy and audit efficiency. Choowan and Daovisan believe that AI-led governance improves compliance and data integrity by allowing for real-time monitoring and automated validation. The results indicate that improving the quality of AI reporting requires strong data governance.

Hence, this study considers data governance quality as a mediating variable between the adoption of AI and financial reporting quality. It ensures consistency and reliability in data input, helping AI systems generate outputs for high-quality reporting.

Organisational readiness

Organisational readiness is the capacity of an organisation to deploy and successfully utilise AI systems. It contains management support, staff ability, technological infrastructure and financial resources. For AI to be adopted, there needs to be both technical competence and organizational buy-in and cultural acceptance.

Readiness means that there is technological preparedness as well as change management, as emphasized by Hradecky et al. (2022). The findings of Bin-Nashwan et al. (2025) and Alaba et al. (2025) demonstrate the important role of readiness in accounting and banking settings. Higher readiness is more likely to be correlated with successful integration and benefits from AI for institutions.

Organisational readiness is expected to further bolster the link between AI adoption and the quality of reporting in financial reporting. AI outputs can be more easily understood and incorporated into the reporting processes at institutions that have sufficient resources and expertise to do so. However, even when they're available, AI can be ineffective if there's a level of readiness deficiency.

Governance oversight

Governance oversight is the accountability of boards, audit committees and internal controls for the monitoring of AI applications in financial reporting. Effective oversight provides that AI systems are used responsibly, transparently and in accordance to organisational and regulatory requirements.

It is argued that responsible AI demands governance mechanisms to hold AI accountable and ensure responsible use (Papagiannidis et al., 2025). Risks of bias, explainability and professional judgement are raised in the work of Kokina et al. (2025) and Commerford et al. (2022), and human oversight is emphasized. If not, the results from AI can be hard to understand or validate, which can affect the quality of reporting.

Good supervision implies oversight of AI outputs to ensure they are validated, documented and reviewed. It also advises on policies relating to data privacy, bias and system reliability. Therefore, the relationship between the use of AI and financial reporting quality is anticipated to be moderated by governance oversight, which is responsible for ensuring the use of AI is controlled and accountable.

Theoretical foundation

The study takes the Technology–Organisation–Environment (TOE) framework as a basis to explain technology adoption based on technological capability, organisational readiness and environmental pressure. AI adoption is the technological context, and organisational readiness and governance oversight are important organisational factors.

Agency theory is also used in conjunction with TOE and highlights the importance of financial reporting quality in minimizing information asymmetry between managers and shareholders. Good reporting makes for transparency and accountability. The institutional theory also addresses how AI is being adopted as a means of meeting regulatory demands, competition and industry standards.

These theories collectively offer a holistic view of the impact of AI on financial reporting quality. They believe that AI can enhance the reporting outcomes, but also the preparedness of the organisation, governance and data governance quality.

Hypotheses Development

Artificial intelligence adoption and financial reporting quality

AI implementation is likely to enhance financial reporting quality by making these financial reporting processes more robust. AI adoption has been linked to lower discretionary accruals and better accrual-cash flow mapping and this indicates that AI-powered systems can help to limit discretion in reporting and increase the transparency between economic reality and accounting numbers. Likewise, Fedyk et al. (2022) find that AI use in audit firms positively impacts assurance outcomes, such as reduced risk of a restatement, which suggests that AI can help enhance financial information verification rather than just streamline repetitive tasks. This connection is not to be exaggerated, however. Despite the progress, AI applications in auditing continue to be subject to concerns around the ability to explain, bias, reliability, privacy and overreliance, as noted by Kokina et al. (2025). Therefore, AI is expected to improve reporting quality when it is integrated into reporting routines, internal controls and professional judgement.

H1: Artificial intelligence adoption has a positive and significant effect on financial reporting quality in financial institutions operating in Nigeria.

Mediating role of data governance quality

AI systems depend on the quality of the data supplied to them. Incomplete, inconsistent or poorly controlled data can produce unreliable outputs, regardless of the sophistication of the technology. Bin-Nashwan et al. (2025) found that big-data governance strengthened the contribution of AI to reporting accuracy and audit efficiency. In financial reporting, sound data governance requires clear data ownership, validation rules, access controls, reconciliations and audit trails. These controls make AI-generated information easier to trace and verify. Data governance quality is therefore expected to provide the pathway through which AI adoption improves financial reporting quality.

H2: Data governance quality mediates the relationship between artificial intelligence adoption and financial reporting quality.

Moderating role of organisational readiness

By embedding organizational readiness as a variable that influences the connection between AI adoption and financial reporting quality, the relationship is expected to be further enhanced. According to Hradecky et al. (2022), the readiness for AI adoption depends on technological readiness, organizational capability and enabling environment. Likewise, Bin-Nashwan et al. (2025) highlight top management support and AI readiness/innovation climate as key factors driving AI adoption in accounting/auditing firms. Alaba et al. (2025) reveal that staff competence, IT infrastructure and regulatory compliance and management support are the factors that facilitate the adoption of AI-driven fraud detection in Nigeria, whereas high implementation cost hinders it. Therefore, AI should yield higher reporting-quality gains when finance, audit, compliance and IT functions can interpret and apply AI output as they have the requisite skills, systems and coordination.

H3: *Organisational readiness positively moderates the relationship between artificial intelligence adoption and financial reporting quality.*

Moderating role of governance oversight

A diverse board can provide multiple perspectives that would allow overall improvement in the decision-making processes, leading to quality financial reporting (Bosede et al., 2026). Governance oversight is expected to strengthen the AI-financial reporting quality relationship because AI-supported reporting raises issues of accountability, assurance, judgement and control. To achieve responsible AI governance, Papagiannidis et al. (2025) suggest that there need to be mechanisms of a structural, relational and procedural nature; that is, the principles of ethics must be institutionalised in the governance of the organisation, in the accountability of the management, in the management of risk and in auditable processes. This is significant as it has an impact on estimates, anomaly detection, reconciliation and risk flag/disclosure review. AI can also undermine accountability if managers are not properly informed about the outputs and do not have a chance to review them. Kokina et al. (2025) point to transparency concerns, reliability issues, bias and overreliance, and Commerford et al. (2022) demonstrate that AI-generated evidence might not be trusted by auditors due to algorithm aversion. Thus, there needs to be effective oversight that verifies inputs to the data, records assumptions, examines AI outputs and holds decision makers accountable for reporting.

H4: *Governance oversight positively moderates the relationship between artificial intelligence adoption and financial reporting quality.*

3. Methodology

Research design

The study adopted a cross-sectional survey design. Data were collected from professionals working in financial institutions operating in Nigeria and used to examine the statistical relationships among AI adoption, data governance quality, organisational readiness, governance oversight and financial reporting quality. Cross-sectional designs provide a snapshot of a population at a particular time and can be used to examine associations among variables, although they cannot establish temporal order or causal effects (Wang & Cheng, 2020). The design was therefore appropriate for testing the direct, mediating and moderating relationships specified in the conceptual model. Accordingly, the findings are interpreted as statistical relationships rather than definitive evidence of causality.

Population and sample

The population comprised employees of financial institutions whose roles related to finance, accounting, audit, compliance, risk management, IT/data analytics, operations or management. These respondents were appropriate because AI-enabled reporting quality requires knowledge of financial-data systems, reporting processes, audit controls and technology-enabled decision support. The institutions surveyed included deposit money banks, insurance companies, microfinance banks, fintech companies, pension and investment institutions, and other regulated financial institutions in Nigeria. The screening criteria ensured that respondents were workers in financial institutions and were familiar with digital, accounting, reporting, audit, compliance or data-management systems. A total of 350 valid responses were received for the final sample. This sample size was considered adequate because Kock and Hadaya (2018) caution against relying mechanically on the “10-times rule” in PLS-SEM and recommend sample-size reasoning based on statistical power and model complexity.

Instrument development

Data were collected using a structured questionnaire developed in three stages. First, the five constructs were defined from the conceptual model and relevant literature. The questionnaire items were selected based on studies on AI adoption and data governance quality (Bin-Nashwan et al., 2025), organisational readiness (Hradecky et al., 2022), governance oversight (Papagiannidis et al., 2025), and financial reporting quality (Johri, 2024; Lisboa et al., 2025). Secondly, the items were formulated to reflect the operational dimensions presented in Table 1 and arranged into sections covering screening information, respondent characteristics and the five study constructs. Thirdly, the draft questionnaire was pilot-tested with 40 professionals drawn from the target population. Their feedback was used to improve clarity and remove ambiguous wording. The construct items were measured on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Pilot testing

The pilot test assessed item clarity and internal consistency. Cronbach’s alpha coefficients ranged from 0.708 to 0.899 across the constructs, exceeding the commonly accepted threshold of 0.70 (Hair et al., 2022). The results indicated acceptable internal consistency. Minor wording changes were consequently made before the questionnaire was administered for the main study.

Measurement of variables

The study measured five constructs: artificial intelligence adoption, data governance quality, organisational readiness, governance oversight and financial reporting quality. Adoption of AI was the independent variable, and financial reporting quality was the dependent variable. The study hypothesized that the quality of data governance is a mediator in AI's influence on reporting quality, and so data governance quality was chosen as the mediator. Organisational readiness and governance oversight were identified as moderators as outcomes of reporting using AI could be influenced by the capacity of organisations and oversight of responsible governance. Table 1 presents the operationalisation of the constructs.

Data analysis technique

The data were analysed using descriptive statistics, reliability analysis, correlation analysis and regression-based structural modelling. Descriptive statistics were used to tabulate respondent characteristics and mean scores of constructs. Cronbach's alpha was used to test internal consistency, as Hair et al. (2022) stated that it serves as a conservative measure of reliability and that composite reliability is beneficial in PLS-SEM. The average variance extracted was used to test convergent validity, and

correlation analysis was used to test bivariate relationships among constructs. The financial reporting quality was measured by the direct influence of AI adoption; the quality of data governance was measured as a mediator variable, and organisational readiness and governance oversight were measured as moderating variables. The model's explanatory power was tested with R^2 and adjusted R^2 . Because of the survey-based data, it was necessary to assess common method variance using Harman's single-factor test, as cautioned by Kock (2015) that common method variance cannot be ruled out by such tests completely.

Table 1: Measurement and operationalisation of constructs

Construct	Code	Role in model	Items	Main measurement areas
Artificial intelligence adoption	AIA	Independent variable	8	AI-enabled automation, advanced analytics, anomaly detection, AI-supported reporting dashboards, AI-supported professional judgement
Data governance quality	DGQ	Mediator	8	Data validation, audit trails, data access control, reconciliation, data ownership, privacy and regulatory compliance
Organisational readiness	ORD	Moderator	8	Top management support, digital infrastructure, staff training, cross-functional collaboration, change management and financial resources
Governance oversight	GOV	Moderator	8	Board/audit committee oversight, internal audit review, AI-risk monitoring, documentation, accountability and ethical control
Financial reporting quality	FRQ	Dependent variable	8	Accuracy, timeliness, completeness, transparency, comparability, verifiability, traceability and reliability

Source: Author's design from empirical review

4. Results and discussion

Respondent and organisational profile

The respondents who completed the questionnaire were 350, which made up the final data. Table 2 reveals that 54.9% of the respondents were males and 42.6% were females. Most respondents were aged 25–34 years (39.7%) and 35–44 years (28.9%), suggesting that the sample was professionally mature. Deposit money banks were the largest institutional group (34.3%), followed by insurance companies (17.1%), microfinance banks (14.3%), fintech companies (14.3%) and pension/investment institutions (14.3%). Respondents were mainly drawn from finance/accounts, internal audit, IT/data analytics, risk management and compliance, which supports the relevance of the responses to AI-enabled reporting processes. Moreover, 65.4% had four or more years of financial-sector experience, indicating appropriate experience with the reporting and control systems.

Descriptive statistics and measurement quality

All construct means are above the neutral point of 3.00, suggesting a generally positive attitude toward AI adoption, data governance, organisational readiness, governance oversight and financial reporting quality, as can be seen in Table 3. Governance oversight ($M = 3.941$) had the highest mean score, followed by data governance quality ($M = 3.893$) and financial reporting quality (3.835). The mean score of AI was

3.539, indicating that the implementation of AI may not be as advanced as that of governance and reporting-control.

Table 2: Respondent and organisational profile

Variable	Category	Frequency	Percentage
Gender	Male	192	54.9
	Female	149	42.6
	Prefer not to say	9	2.6
Age	Below 25 years	24	6.9
	25–34 years	139	39.7
	35–44 years	101	28.9
	45–54 years	58	16.6
	55 years and above	28	8.0
Institution type	Deposit money banks	120	34.3
	Insurance companies	60	17.1
	Microfinance banks	50	14.3
	Fintech companies	50	14.3
	Pension/investment institutions	50	14.3
	Other regulated financial institutions	20	5.7
Department/unit	Finance/accounts	78	22.3
	Internal audit	62	17.7
	IT/data/analytics	60	17.1
	Risk management	46	13.1
	Compliance	44	12.6
	Other units	60	17.2
Work experience	Less than 1 year	39	11.1
	1–3 years	82	23.4
	4–6 years	83	23.7
	7–10 years	67	19.1
	Above 10 years	79	22.6

Source: Author's computation: 2026

Table 3: Descriptive statistics, reliability and validity results

Construct	N	Mean	SD	A	CR	AVE	Interpretation
AIA	350	3.539	0.716	0.909	0.926	0.612	Reliable and valid
DGQ	350	3.893	0.437	0.779	0.838	0.394	Reliable; AVE caution
ORD	350	3.780	0.550	0.856	0.888	0.498	Reliable; AVE marginal
GOV	350	3.941	0.465	0.819	0.863	0.441	Reliable; AVE caution
FRQ	350	3.835	0.487	0.843	0.880	0.478	Reliable; AVE marginal

Note: AIA = artificial intelligence adoption; DGQ = data governance quality; ORD = organisational readiness; GOV = governance oversight; FRQ = financial reporting quality; α = Cronbach's alpha; CR = composite reliability.

The reliability was satisfactory for all constructs. AI adoption had excellent reliability ($\alpha = 0.909$; CR = 0.926), while data governance, organisational readiness, governance oversight and financial reporting quality had acceptable to very good reliability. Some AVE values, however, were below or near 0.50, so

the convergent validity should be interpreted with caution in combination with the theoretical coherence and reliability of the measures.

Common method bias

Since the study relied on survey responses, common method bias was assessed using Harman's single-factor test. The first non-rotated factor accounted for 26.14% of the total variance, which is below the 50% criterion. This indicates that the majority of the covariance of the items was not due to a single dominant factor. But as Kock (2015) cautions, this is not seen as conclusive evidence of the absence of common method variance.

Correlation analysis and hypothesis testing

Table 4 shows that there are significant positive correlations between constructs in Panel A. There was a positive relationship between financial reporting quality and adoption of AI ($r = 0.560$, $p < 0.01$). There were also positive correlations between financial reporting quality and data governance quality ($r = 0.507$), organisational readiness ($r = 0.518$) and governance oversight ($r = 0.322$). The findings confirm the hypothesized relationships between AI, governance, readiness, and reporting quality, but do not prove cause-and-effect relationships.

Table 4: Correlation matrix and hypothesis-testing results

Panel A: Correlation matrix

Construct	AIA	DGQ	ORD	GOV	FRQ
AIA	1.000				
DGQ	0.334**	1.000			
OR	0.529**	0.451**	1.000		
GOV	0.187**	0.339**	0.264**	1.000	
FRQ	0.560**	0.507**	0.518**	0.322**	1.000

Note: ** $p < 0.01$.

Panel B: Hypothesis-testing results

Hyp.	Path	Effect	p-value / CI	Decision
H1	AIA $\rightarrow$ FRQ	0.381	$p < 0.001$	Supported
H2	AIA $\rightarrow$ DGQ $\rightarrow$ FRQ	0.082	95% CI [0.055, 0.113]	Supported
H3	AIA $\times$ ORD $\rightarrow$ FRQ	-0.080	$p = 0.100$	Not supported
H4	AIA $\times$ GOV $\rightarrow$ FRQ	-0.145	$p = 0.014$	Not supported (opposite sign)
Full model	Predictors $\rightarrow$ FRQ	$R^2 = 0.473$	Adj. $R^2 = 0.463$	Moderate explanatory power

The results of the hypothesis testing are displayed in panel B. Thus, the positive and significant relationship between the adoption of AI and financial reporting quality supported H1 ($\beta = 0.381$, $p < 0.001$). Support for H2 was also high (effect = 0.082, 95% CI [0.055, 0.113] via data governance). H3 was not supported as the interaction of AI adoption with organisational readiness was not significant ($\beta = -0.080$, $p = 0.100$). H4 did not meet the criteria for the relationship of AI adoption with governance oversight interaction because it was significant but negative ($\beta = -0.145$, $p = 0.014$). There was moderate explanatory power in the full model, with 47.3% of the variance in financial reporting quality being explained.

Overall, AI adoption improves financial reporting quality directly and indirectly through data governance. However, the moderation results show that organisational readiness and governance oversight operate more complexly than initially expected.

Hypothesis One: AI adoption and financial reporting quality

H1 proposed that AI adoption would have a positive and significant effect on financial reporting quality. The result supported H1 ($\beta = 0.381$, $p < .001$). Higher reported levels of AI adoption were associated with better financial reporting quality among the institutions studied. This finding is consistent with Anantharaman et al. (2023), who linked AI adoption with lower discretionary accruals and improved accrual-cash-flow matching. It also agrees with Fedyk et al. (2022), who found that investment in AI improved audit quality and efficiency. In the present study, the result indicates that AI can support reporting activities such as reconciliation, anomaly detection, transaction review and the evaluation of accounting estimates. However, because the study used cross-sectional perceptual data, the result represents a positive statistical relationship and should not be interpreted as definitive proof that AI alone caused the improvement. This position is also supported by Gbenga and Olabisi (2025) when they observed that AI is not an end in itself but a transformative enabler that modernizes each stage of the tax cycle – data collection, assessment, compliance monitoring, auditing, enforcement, and reporting. This transformative tendency is also felt in the financial reporting process.

Hypothesis Two: Mediating role of data governance quality

H2 proposed that data governance quality would mediate the relationship between AI adoption and financial reporting quality. The indirect effect was significant (effect = 0.082, 95% CI [0.055, 0.113]); therefore, H2 was supported. The result shows that AI adoption contributes to financial reporting quality partly through the institution's data-governance arrangements. This finding agrees with Bin-Nashwan et al. (2025), who found that big-data governance supported the contribution of AI to reporting accuracy and audit efficiency. Data validation, ownership, access controls, reconciliation and audit trails make AI-generated information easier to verify and use in reporting. Data governance is therefore not a separate administrative activity. It is one of the mechanisms through which AI adoption is translated into more reliable financial reporting.

Hypothesis Three: Moderating role of organisational readiness

H3 proposed that organisational readiness would positively moderate the relationship between AI adoption and financial reporting quality. The interaction effect was not statistically significant ($\beta = -0.080$, $p = .100$); therefore, H3 was not supported. This means that the relationship between AI adoption and reporting quality did not differ significantly across the reported levels of organisational readiness in the sample. The result does not mean that readiness is unimportant. Hradecky et al. (2022), Bin-Nashwan et al. (2025) and Alaba et al. (2025) show that infrastructure, staff competence and management support can influence whether an organisation adopts AI successfully. Readiness may therefore be more important during the adoption and implementation stages than in strengthening the relationship after AI has been introduced. It is also possible that regulated financial institutions share a minimum level of digital infrastructure and professional expertise, reducing differences in readiness. This explanation remains tentative and should be tested in future studies.

Hypothesis Four: Moderating role of governance oversight

H4 proposed that governance oversight would positively moderate the relationship between AI adoption and financial reporting quality. The interaction effect was statistically significant but negative ($\beta = -0.145$, $p = .014$). H4 was therefore not supported because the observed direction was contrary to the proposed positive relationship. In this sample, stronger governance oversight weakened the positive relationship between AI adoption and financial reporting quality. One possible explanation is that oversight may be more intensive in institutions where AI-related risks or reporting problems are already

more visible. Oversight may also become compliance-centred and procedural, slowing the use of AI outputs without necessarily improving their quality. Papagiannidis et al. (2025) maintain that responsible AI governance requires structural, relational and procedural mechanisms. The present finding does not support reducing oversight. Instead, it indicates that oversight should be technically informed, proportionate and focused on specific risks rather than relying mainly on restrictions. Because the moderation analysis does not establish why the negative relationship occurred, these explanations should be treated cautiously.

5. Conclusion

This study examined the relationship between AI adoption and financial reporting quality in financial institutions operating in Nigeria. It also tested data governance quality as a mediator and organisational readiness and governance oversight as moderators. Based on 350 valid responses, AI adoption had a positive and significant relationship with financial reporting quality. Data governance quality partly mediated this relationship, indicating that AI contributes more effectively to reporting when the underlying data are accurate, controlled and traceable. Organisational readiness did not significantly moderate the relationship. Governance oversight produced a significant but negative moderating effect, contrary to the proposed positive relationship. These findings show that adopting AI does not by itself guarantee better financial reporting. Its reporting value depends particularly on data governance and on how oversight is designed and exercised. Because the study used cross-sectional perceptual data, the results should be interpreted as statistical relationships rather than definitive causal effects.

The study recommended that while financial institutions should continue to invest in emerging AI-enabled technologies, there is a need to strengthen their data governance structures to promote data integrity and accuracy of data fed into these AI-enabled Technologies in the process of financial reporting. This is necessary as the quality of AI-driven financial reporting depends largely on the integrity of the human element involved in the process. AI adoption alone may not bring the desired benefit of improvement in the quality of financial reporting; this should be preceded by a sound data governance system in place, such as accurate data, validation controls, audit trails, data and access controls, reconciliation and data accountability.

6. Declarations

Conflict of Interest

The author declares no conflict of interest.

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Data Availability

Data that underlie the conclusions of this study are available on reasonable request, subject to confidentiality considerations and to the protection of the anonymity of respondents and institutions.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

As part of the preparation of this work, the author entered the name ChatGPT developed by OpenAI to refine language, organise structure, edit and improve readability. The author developed the research focus, reviewed the literature, conducted and interpreted the analysis, verified the content and edited the manuscript as needed. The author takes full responsibility for the content of the published article.

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