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AI-Enabled Compliance Monitoring and Adherence to Financial Regulations in Nigeria's Federal Public Sector

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Abstract

Compliance with financial regulations is central to public accountability, yet monitoring adherence across ministries, departments and agencies is difficult at the scale and complexity of Nigeria's federal public sector. This study examines whether documented adoption of artificial intelligence (AI)-enabled compliance monitoring is associated with adherence to financial regulations in Nigeria's federal public sector. A balanced panel of five federal institutions, the Federal Ministry of Finance, the Office of the Accountant-General of the Federation, the Federal Inland Revenue Service, the Central Bank of Nigeria and the Bureau of Public Procurement is observed over 2015–2024. Documentary evidence from annual reports, audit-related documents and AI-implementation documents is scored on a five-point (0–4) rubric and analysed with pooled, fixed-effects, trend-adjusted, first-difference and lagged regressions, interpreted through agency theory. AI-enabled compliance monitoring is positively and significantly associated with regulatory compliance (pooled $\beta = 0.719$, $R^2 = 0.923$; fixed-effects $\beta = 0.742$, within $R^2 = 0.858$). The association remains positive and significant after controlling for a common time trend ($\beta = 0.629$), in first differences ($\beta = 0.554$) and when monitoring is lagged one year ($\beta = 0.657$). A conservative reading is that one additional point of monitoring adoption is associated with roughly 0.55 to 0.65 points higher regulatory compliance. Because the design is observational, the measures are documentary indices, and the sample is small and purposively selected, the results indicate association rather than proven causation and are interpreted for the five institutions examined rather than for all federal ministries, departments and agencies. The findings support investment in AI-enabled monitoring as one component of a functioning compliance chain, accompanied by data quality, regulatory clarity, staff capacity, governance arrangements and human review.

Keywords: *Artificial intelligence; compliance monitoring; financial regulations; regulatory adherence; public financial management; Nigeria.*

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Introduction

Public institutions are required to manage public funds in accordance with applicable laws, financial regulations, procurement requirements, treasury directives and accounting standards. Compliance with these requirements is essential for credible financial reporting, effective resource management and public accountability. Nevertheless, monitoring adherence across ministries, departments and agencies can be difficult because of the volume of transactions, fragmented information systems, inconsistent documentation and limitations in institutional capacity.

Nigeria's public financial management environment illustrates the importance of this challenge. Audit findings concerning federal financial statements have highlighted issues involving the consolidation of financial information, the use of unaudited balances and the implementation of accrual-based International Public Sector Accounting Standards (Office of the Auditor-General for the Federation, 2024). Such issues demonstrate the continuing need to strengthen financial reporting controls and regulatory compliance. They do not, however, establish that technological limitations alone account for the observed weaknesses.

Traditional compliance monitoring often relies on periodic inspections, manual verification and sample-based auditing (Abdullahi & Abubakar, 2024). Although these approaches remain important, they may not provide sufficiently timely coverage of high-volume financial transactions. Artificial intelligence (AI) offers opportunities to improve monitoring through automated rule checking, anomaly detection, transaction classification, document analysis and the identification of potentially non-compliant activities. Machine learning and natural language processing can assist institutions in identifying unusual transaction patterns and extracting relevant requirements from financial and regulatory documents (Adewale et al., 2023).

AI-enabled monitoring is not automatically effective. Its contribution depends on data quality, the clarity of applicable regulations, system integration, staff competence and appropriate oversight. Poorly designed systems may produce false alerts, reproduce errors in historical data, or make decisions that are difficult to explain. Consequently, the adoption of AI must be considered alongside the institutional and governance arrangements needed to make its outputs reliable and actionable.

Although AI adoption in accounting, auditing, fraud detection and financial risk management has received growing attention, empirical evidence on its relationship with regulatory compliance in Nigeria's federal public sector remains limited. In particular, there is a need for institution-level analysis that examines whether the association between AI-enabled compliance monitoring and regulatory adherence persists after accounting for institutional differences and common changes over time.

Statement of the Problem

Compliance monitoring is central to public financial accountability, but it is difficult to sustain at the scale and complexity of Nigeria's federal public sector. Transactions are numerous and dispersed across ministries, departments and agencies; information systems are fragmented; documentation is inconsistent; and institutional capacity varies. Traditional monitoring methods, periodic inspections, manual verification and sample-based

auditing, remain important but may not provide sufficiently timely coverage of high-volume transactions. The audit findings on federal financial statements (Office of the Auditor-General for the Federation, 2024) show that weaknesses in financial reporting controls persist, and that the need to strengthen monitoring is practical rather than theoretical.

AI-enabled compliance monitoring is often proposed as a response, but the evidence base is limited in three respects. First, much of the existing literature examines AI in accounting, auditing or fraud detection generally, rather than compliance monitoring specifically. Second, the evidence that does exist is dominated by descriptive, single-site or non-Nigerian studies, so it is unclear whether the pattern holds for Nigerian federal institutions. Third, there is little panel evidence on whether documented AI adoption and documented regulatory adherence move together once institutional differences and common temporal trends are accounted for.

A further problem concerns measurement. Compliance is not the same as detection: an institution may flag more irregularities because its monitoring has improved, without the underlying incidence of non-compliance having fallen. An index of documented adherence to financial regulations is therefore a measure of documented compliance, not of the underlying incidence of non-compliance, and the relationship between AI-enabled monitoring and adherence must be interpreted with that distinction in mind.

Accordingly, this study examines the association between documented AI-enabled compliance monitoring and adherence to financial regulations in five Nigerian federal institutions over the period 2015–2024, and assesses whether the association is robust to institutional differences, common temporal trends and potential reverse causality.

Aim and Objectives of the Study

The main aim of this study is to examine the association between documented AI-enabled compliance monitoring and adherence to financial regulations in Nigeria's federal public sector.

The specific objective is:

i. To examine the association between documented AI-enabled compliance monitoring (AICM) and adherence to financial regulations (FRQ3) in Nigeria's federal public sector.

Research Question

The study is guided by the following research question:

i. What is the association between documented AI-enabled compliance monitoring and adherence to financial regulations in Nigeria's federal public sector?

Research Hypothesis

The study tests the following hypothesis at the 5% level of significance:

H_0: Documented AI-enabled compliance monitoring is not significantly associated with adherence to financial regulations in Nigeria's federal public sector.

H_1: Documented AI-enabled compliance monitoring is positively and significantly associated with adherence to financial regulations in Nigeria's federal public sector.

Significance of the Study

Policy: the findings will provide evidence on whether documented AI-enabled compliance monitoring is associated with adherence to financial regulations in Nigeria's federal public sector, and will inform decisions about investment in monitoring technology, data infrastructure and regulatory clarity.

Practice: the study will identify whether federal institutions with higher documented AI adoption show better documented compliance, and will highlight the conditions, data quality, regulatory clarity, system integration, staff competence and oversight, on which the benefits of AI-enabled monitoring depend. It will recommend the publication of operational indicators (exceptions flagged, cases resolved, compliance rates) so that the effects of adoption can be tracked directly.

Research: the study will contribute panel evidence for Nigerian federal institutions to a literature dominated by descriptive, single-site and non-Nigerian studies, and will identify directions for future research, including transaction-level data, false-positive burdens and causal designs.

Scope of the Study

The study covers five purposively selected federal institutions: the Federal Ministry of Finance, the Office of the Accountant-General of the Federation, the Federal Inland Revenue Service, the Central Bank of Nigeria and the Bureau of Public Procurement. Each institution is observed annually from 2015 to 2024, yielding a balanced panel of 50 institution-year observations. The study is limited to documentary evidence, annual reports, audit-related documents and AI-implementation documents, and does not collect survey or interview data. The findings are interpreted for the selected institutions and the period examined, not for all federal ministries, departments and agencies.

Review of Related Literature

AI and Compliance Monitoring

AI-enabled compliance monitoring involves the use of computational systems to identify, evaluate and report possible departures from applicable rules and standards. These systems may incorporate rule-based automation, machine learning, natural language processing, anomaly detection and automated reporting.

Rule-based systems compare transactions or documents against predefined requirements. Machine learning systems can identify patterns associated with previously observed irregularities, while natural language processing

can support the analysis of regulatory documents, financial disclosures and audit findings (Akanbi & Yusuf, 2024). When appropriately integrated, these technologies can support more frequent monitoring and help officials prioritise transactions requiring further investigation.

Gibson et al. (2020) discuss the opportunities and challenges associated with AI-enabled compliance monitoring, including automation, risk identification and the difficulties of interpreting system outputs. These considerations are relevant to public financial management, where monitoring tools must operate within established legal and administrative requirements.

However, technology should be viewed as a complement to, rather than a replacement for, effective internal controls and professional judgment. AI-generated alerts require validation, and institutions must establish procedures for correcting errors, investigating suspected violations and documenting remedial action.

AI Adoption and Financial Accountability in Nigeria

The potential benefits of AI-enabled monitoring are particularly relevant to Nigeria's federal public sector, where financial accountability depends on effective coordination among institutions responsible for budgeting, treasury operations, revenue administration, procurement and auditing.

Adewale et al. (2023) examine AI-based compliance monitoring in Nigerian federal agencies, while Akinola and Lawal (2023) consider AI adoption and public sector financial reporting quality. These studies are relevant to the broader proposition that digital monitoring may support financial controls and reporting processes.

Institutional readiness also matters. AI-enabled monitoring requires reliable digital records, suitable information systems, trained personnel and clear responsibility for acting on system-generated alerts. Institutions with stronger digital capabilities may be better positioned to deploy monitoring tools effectively than those with fragmented information systems or limited technical expertise (Cheng et al., 2022; Uzor & Bello, 2021).

Consequently, the relationship between AI adoption and compliance should not be assumed to be uniform across institutions. The effectiveness of monitoring may depend on institutional resources, the quality of the underlying data, management support and the extent to which regulatory requirements can be represented in a form suitable for automated checking.

Regulatory Governance, Transparency and Accountability

AI-enabled compliance monitoring raises important questions about transparency, accountability and data protection. Automated systems can improve the consistency and speed of routine checks, but their outputs may be difficult to interpret when they rely on complex models (Lee & Kim, 2021; Mehta & Shah, 2020). This creates challenges when public officials must explain why a transaction was flagged or demonstrate that a compliance decision followed applicable rules.

Peters et al. (2020) discuss ethical challenges associated with AI-based decision-making in compliance monitoring. These challenges reinforce the importance of explainability, human review, appropriate data access controls and clearly assigned responsibility for decisions made with technological assistance.

In public institutions, compliance systems should therefore be designed around auditable procedures. Their outputs should be documented, material alerts should be reviewable, and officials should retain responsibility for decisions that require legal interpretation or professional judgment. These safeguards can help prevent automated monitoring from becoming an opaque process that weakens rather than strengthens accountability.

Theoretical Framework: Agency Theory

Agency theory explains relationships in which one party delegates responsibilities to another and faces difficulties observing or verifying the latter's actions. In public financial management, citizens and oversight bodies depend on public officials to manage resources in accordance with established rules and public objectives.

Jensen and Meckling (1976) explain how monitoring arrangements can reduce information asymmetry and agency-related costs. Applied to public financial management, AI-enabled compliance monitoring may reduce the cost of examining transactions, increase the frequency of checks and help identify departures from financial regulations.

The theoretical expectation is that more effective monitoring will be associated with stronger regulatory adherence. However, the extent of this relationship depends on whether identified problems are investigated and corrected. The study therefore hypothesises that AI-enabled compliance monitoring is positively associated with adherence to financial regulations in Nigeria's federal public sector.

Empirical Review

Tookitaki (2024), in *The Role of Technology in Strengthening AML Compliance in Nigeria*, used a descriptive analysis of machine learning applications in anti-money laundering (AML) compliance. The article detailed how AI tools analyse financial transactions in real time to flag suspicious activities, improving the efficiency and reliability of AML efforts critical to public financial regulation.

Nwatu et al. (2024) developed a model in *A Robust Model for Integrating Artificial Intelligence into Financial Risk Management: Addressing Compliance, Accuracy and Scalability Issues*. Their empirical study used simulations to validate AI's utility in public financial risk management. The model yielded improvements in regulatory adherence and financial data precision, affirming the role of AI in compliance systems.

Uzougbo et al. (2024) explored *Cybersecurity Compliance in Financial Institutions: A Comparative Analysis of Global Standards and Regulations*. Their study employed a comparative legal framework to benchmark Nigerian institutions against international standards. Institutions applying AI-enabled compliance tools reported fewer data breaches and higher levels of regulatory conformity.

Ademola (2024) published a policy analysis titled *Harnessing AI and Cybersecurity: Transforming Nigeria's Legal System towards Transparency and Accountability*. Using case study methodology, the paper illustrated how public legal institutions use AI in automation and fraud detection. The results showed reduced human error and stronger adherence to financial compliance norms.

Odonkor et al. (2024), in *Artificial Intelligence for Financial Accountability and Governance in the Public Sector: Strategic Opportunities and Challenges*, adopted a mixed-methods approach to assess how AI supports financial governance. Their study emphasised that AI-driven systems reduce loopholes in public expenditure and foster proactive compliance monitoring across public institutions.

Platform Africa (2024), in *How RegTech Together with AI is Transforming Regulatory Compliance*, employed a case study methodology using real-world examples from financial institutions. The study demonstrated that AI-driven regulatory updates and predictive analytics enable better compliance management, which is particularly beneficial for Nigerian institutions facing resource constraints.

A and D Forensics (2024), in their report *Navigating Compliance in Nigeria*, summarised insights from a Nigerian Financial Intelligence Unit (NFIU) session, adopting a qualitative report review approach. The session highlighted how AI tools analysing suspicious transaction reports (STRs) have improved response times and accuracy, with AI adoption linked to faster resolution and fewer compliance failures, underscoring AI's positive effect on regulatory adherence.

Shobanjo (2024), in *The Future of Financial Regulations in Nigeria*, explored the implementation of AI tools to enhance startup compliance using a descriptive case study approach. The study highlighted Prembly's Compliance Tracker, an AI-based tool automating regulatory monitoring, and found that institutions adopting it experienced reduced regulatory breaches and faster audit cycles, demonstrating AI's positive impact on compliance outcomes.

Uzougbo et al. (2024), in *Legal Accountability and Ethical Considerations of AI in Financial Services*, employed a conceptual analysis methodology combined with expert validation. The study focused on governance ethics in AI systems and highlighted the importance of ethical AI frameworks for maintaining lawful adherence and reducing bias in compliance automation.

Obiora and Agwu (2024) conducted a qualitative study titled *Artificial Intelligence and Financial Regulation: A Review of Institutional Readiness in Nigeria*, based on interviews with senior officials at the Central Bank of Nigeria and EFCC. They found that while AI-based tools were increasingly adopted, there remained a disconnect between system capability and institutional readiness. The study recommended strategic training and infrastructure development to fully leverage AI in regulatory compliance.

Onyeama (2024) conducted a study titled *Credit Card Fraud Detection in the Nigerian Financial Sector: A Comparison of Unsupervised TensorFlow-Based Anomaly Detection Techniques, Autoencoders and PCA Algorithm*. This research compared AI techniques using real transaction data from Nigerian banks. Onyeama employed a quantitative design

using unsupervised learning to assess fraud detection efficiency. The findings showed that autoencoders outperformed PCA in anomaly detection, enhancing institutional compliance with financial monitoring expectations.

Adelekan et al. (2024) studied the integration of AI in cybersecurity audits in Nigerian banks, highlighting its role in improving compliance with financial regulations. Their paper, *Cybersecurity Audits and Performance of Selected Deposit Money Banks in Nigeria*, employed a qualitative approach, analysing audit practices and risk compliance systems. The authors found that AI-based audit mechanisms improved internal controls and facilitated timely regulatory reporting, reducing lapses in financial governance among public institutions.

Ebrusike and Anyasi (2024) assessed Nigeria's institutional preparedness for AI regulation through their work titled *The Status of AI Regulation in Nigeria*. The study employed a policy analysis method focusing on frameworks developed by NITDA and the National Centre for Artificial Intelligence and Robotics (NCAIR). Their findings revealed that while significant progress had been made in AI policy drafting, implementation gaps remain, particularly in public financial oversight. They concluded that robust compliance monitoring tools powered by AI are essential to enforce these evolving regulations.

Research Gap

The literature reviewed demonstrates that AI-based methods have been applied to compliance monitoring and that regulatory adherence depends on effective internal controls, institutional readiness and governance arrangements. However, three issues warrant further investigation. First, much of the existing evidence is descriptive, single-site or drawn from non-Nigerian settings (e.g., Gibson et al., 2020; Tookitaki, 2024; Platform Africa, 2024), which does not necessarily establish whether documented AI adoption is associated with improved regulatory compliance in Nigerian federal institutions. Second, several studies rely on simulations, interviews or qualitative reviews (e.g., Nwatu et al., 2024; Obiora & Agwu, 2024; PLSI, 2024), and perception-based evidence may not correspond to documented compliance outcomes. Third, the relationship between AI adoption and compliance may be influenced by institutional differences and broader improvements in the financial control environment, making it important to examine whether any observed association persists under alternative empirical specifications.

The gap, then, is empirical rather than conceptual: whether documented AI-enabled compliance monitoring and documented regulatory adherence move together in Nigerian federal institutions, once institutional differences and common temporal trends are accounted for, has not been examined with institution-level, multi-year documentary evidence. This study addresses the gap by examining the association between documented AI-enabled compliance monitoring and a composite measure of adherence to financial regulations in five selected Nigerian federal public institutions over the period 2015–2024. The longitudinal design enables the study to examine changes over time and assess the stability of the observed association under alternative specifications. Although the design cannot establish a definitive causal effect, it provides an empirical basis for evaluating whether documented AI adoption and regulatory compliance move together after accounting for time-invariant institutional differences and common temporal trends.

Methodology

Research Design and Sample

The study employs a longitudinal archival research design to examine the association between documented AI-enabled compliance monitoring and adherence to financial regulations in Nigeria's federal public sector. Five institutions were selected purposively because of their central roles in public financial management and the availability and consistency of documentary evidence: the Federal Ministry of Finance (FMF), the Office of the Accountant-General of the Federation (OAGF), the Federal Inland Revenue Service (FIRS), the Central Bank of Nigeria (CBN) and the Bureau of Public Procurement (BPP). The observation period covers 2015–2024. Five institutions observed over ten years produce a balanced panel of 50 institution-year observations, with complete documentary coverage confirmed for all 50 institution-year cells.

Data were abstracted from annual financial reports, audit-related documents, institutional publications and official documentation concerning AI implementation. The study uses documentary evidence rather than interviews or a survey of public officials. The sample is not probability-based, and results apply to these institutions, not to all federal ministries, departments and agencies.

Measurement of Variables

The analysis uses two composite indices scored on a five-point (0–4) scale, with higher scores indicating greater documented adoption or stronger documented adherence.

AI-enabled compliance monitoring (AICM) is the explanatory variable. It represents the documented extent to which an institution uses AI-enabled systems to monitor compliance with financial rules and identify potential violations. The rubric assigns scores as follows: 0 = no documentary evidence of AI-enabled compliance monitoring; 1 = policy statement or strategic intention only, with no implementation; 2 = pilot, tender or procurement stage documented; 3 = partial deployment in at least one compliance function; 4 = full documented deployment across core compliance monitoring operations. Component indicators include documented use of AI for automated rule checking, anomaly detection, transaction classification and document analysis.

Financial regulatory compliance (FRQ3) is the dependent variable. It represents the documented extent of adherence to applicable financial regulations and reporting standards. The rubric assigns scores on the same 0–4 scale, applied to two dimensions: (i) documented compliance with financial reporting requirements and (ii) documented strength of internal control and audit follow-up. The composite FRQ3 score is the mean of the two dimension scores. The FRQ3 scoring procedure distinguishes, to the extent permitted by the available records, between the detection of potential violations and documented adherence, so that improved monitoring capacity is not conflated with improved compliance.

Both variables are ordinal-derived indices. The regression coefficients are therefore interpreted in index points, not as percentage reductions in violations or as percentage changes in compliance.

To support scoring consistency, all documents were coded by the researcher using the rubrics described above. A second coder independently scored a random subset of 20% of the institution-year observations, and discrepancies were resolved by re-examining the underlying documentary evidence. The final scores reflect the reconciled assessments.

Model Specification and Estimation

The baseline relationship is specified as:

$$FRQ3_{it} = \beta_0 + \beta_1 AICM_{it} + \varepsilon_{it}$$

where $FRQ3_{it}$represents regulatory compliance for institution $i$in year t, $AICM_{it}$represents documented AI-enabled compliance monitoring, $\beta_0$is the intercept, $\beta_1$is the coefficient measuring the association between monitoring adoption and compliance, and $\varepsilon_{it}$is the error term. The coefficient of primary interest is β_1. A positive coefficient indicates that higher monitoring scores are associated with higher regulatory compliance scores.

The analysis uses several specifications to assess the stability of the estimated relationship. First, pooled ordinary least squares (OLS) estimates the overall association between the two indices. Second, institution fixed-effects regression accounts for time-invariant differences across the five institutions. Third, a trend-adjusted fixed-effects model includes a linear year trend to account for common changes over time:

$$FRQ3_{it} = \alpha_i + \beta_1 AICM_{it} + \beta_2 Trend_t + \varepsilon_{it}$$

Fourth, a first-difference specification examines whether changes in monitoring adoption are associated with changes in compliance:

$$\Delta FRQ3_{it} = \beta_1 \Delta AICM_{it} + \Delta\varepsilon_{it}$$

Finally, a lagged model examines whether monitoring adoption in the preceding year is associated with compliance in the following year:

$$FRQ3_{it} = \alpha_i + \beta_1 AICM_{i,t-1} + \varepsilon_{it}$$

These alternative specifications provide complementary assessments of the stability of the estimated association. However, neither differencing nor lagging the explanatory variable, on its own, establishes a causal relationship.

HC3 heteroskedasticity-robust standard errors are used because they are preferable to clustered errors when there are only five clusters. A Hausman test yields $\chi^2 = 2.354$, $p = 0.125$, indicating that the test does not reject the random-effects specification at the 5% significance level. Fixed effects are nevertheless retained as the principal conservative specification, because institutional mandates and data capacity plausibly correlate with adoption.

Statistical significance is assessed at the 5% level. The results are interpreted with consideration of the small number of institutions, the documentary basis of the measurements and the observational nature of the research design. In particular, the use of heteroskedasticity-consistent standard errors does not, by itself, eliminate concerns about serial dependence or common shocks in a panel containing only five institutions, so the reported p-values are treated as lower bounds on uncertainty rather than as exact. The estimates are therefore interpreted conservatively:

the pooled and fixed-effects coefficients are treated as upper references, the trend-adjusted and first-difference coefficients as the more demanding tests, and the lagged coefficient as evidence on timing rather than on contemporaneous association.

Results

Descriptive Statistics

The mean regulatory compliance score is 3.69 (SD = 0.52), and the mean AI-enabled compliance monitoring score is 3.83 (SD = 0.70). The average compliance score increases from 3.01 in 2015 to 4.35 in 2024, while the average monitoring score increases from 2.91 to 4.73 over the same period. The correlation between the two indices is 0.96, reflecting this common upward drift. The Central Bank of Nigeria and Federal Inland Revenue Service record the highest average monitoring and compliance scores, while the Bureau of Public Procurement records the lowest.

The high correlation and the parallel upward trends in both series motivate the estimation strategy set out: the trend and first-difference specifications are needed to assess how much of the raw association survives once common temporal drift is removed.

Table 1. Descriptive statistics and correlation matrix (N = 50)

Variable	Mean	SD	Min	Max	1	2
1. FRQ3 (regulatory compliance)	3.69	0.52	2.00	5.00	1.00	
2. AICM (AI-enabled compliance monitoring)	3.83	0.70	2.00	5.00	0.96	1.00

Note: FRQ3 = financial regulatory compliance; AICM = AI-enabled compliance monitoring. Scores are composite indices on a 0–4 rubric, rescaled here to a 1–5 reporting range for presentation. The final two columns report pairwise Pearson correlations; the diagonal is 1.00 by construction and the upper triangle is left blank. Source: Author's computation from the panel dataset.

Main Estimates

Table 2 reports the main estimates across the five specifications. AI-enabled compliance monitoring has a positive and statistically significant coefficient in every specification. In the pooled model, the coefficient is 0.719 (robust SE = 0.030, $p < 0.001$), indicating that a one-point increase in the AI-enabled compliance monitoring index is associated with a 0.719-point increase in the regulatory compliance index; the model has an R^2 of 0.923 and an adjusted R^2 of 0.922. The institution fixed-effects model produces a coefficient of 0.742 (robust SE = 0.033), indicating that the positive association remains when time-invariant differences between institutions are taken into account. The trend-adjusted model produces a coefficient of 0.629 (robust SE = 0.086), suggesting that part of the baseline association reflects changes occurring across institutions over time, while the association remains positive and significant. The first-difference model produces a coefficient of 0.554 (robust SE = 0.096), indicating that changes in monitoring adoption are positively associated with changes in regulatory compliance. The one-year lagged model produces a coefficient of 0.657 (robust SE = 0.066), suggesting that monitoring adoption in the preceding year is

positively associated with compliance in the subsequent year; lagging the explanatory variable alone does not establish causality or eliminate possible confounding factors.

Table 2. AI-enabled compliance monitoring and regulatory compliance (dependent variable: FRQ3)

Specification	Coefficient on AICM	Robust SE	p-value	N
Pooled OLS	0.719	0.030	< 0.001	50
Fixed effects (institution)	0.742	0.033	< 0.001	50
Fixed effects + linear trend	0.629	0.086	< 0.001	50
First differences	0.554	0.096	< 0.001	45
Fixed effects, AICM lagged one year	0.657	0.066	< 0.001	45

Note: Pooled model: $R^2 = 0.923$, adjusted $R^2 = 0.922$. Standard errors for all models except the pooled model are HC3-robust. The first-difference and lagged models lose the first year for each institution (5 observations), yielding N = 45. Coefficients are reported in index points. Source: Author's computation from the panel dataset.

Taken together, the estimates provide consistent evidence of a positive statistical association across the five model specifications. On this evidence the null hypothesis of no association (H_o) is rejected in favour of the alternative (H_1).

Robustness and Diagnostic Results

The reported diagnostic results include a Durbin–Watson statistic of 1.86, a Breusch–Pagan test p-value of 0.161 and a Jarque–Bera test p-value of 0.953. The Durbin–Watson statistic is within the conventional 1.5–2.5 band, indicating no strong first-order autocorrelation; the Breusch–Pagan test provides no evidence of heteroskedasticity; and the Jarque–Bera test does not reject normality of residuals. These results do not indicate statistically significant evidence of the specific problems tested, but they should not be interpreted as proof that the models satisfy every relevant assumption.

The trend-adjusted, first-difference and lagged estimates remain positive. Relative to the fixed-effects coefficient of 0.742, the trend-adjusted coefficient of 0.629 retains approximately 84.8 per cent of its magnitude. This reduction suggests that common temporal changes may explain part of the observed association. The remaining positive relationship is consistent with the proposition that monitoring adoption and compliance move together beyond their shared time trend. It does not, by itself, establish that the monitoring systems caused the improvement. Taking the trend-adjusted and first-difference estimates together, a conservative reading is that one additional point of monitoring adoption is associated with roughly 0.55 to 0.65 points higher regulatory compliance.

Discussion

The findings indicate a strong positive association between documented AI-enabled compliance monitoring and regulatory compliance in the five selected federal institutions. The consistency of the coefficient signs across pooled, fixed-effects, trend-adjusted, first-difference and lagged specifications suggests that the relationship is not confined to a single estimation method.

One possible explanation is that compliance monitoring is closely connected to the outcome being measured. Systems designed to check transactions and documents against explicit requirements may be particularly relevant to a compliance index based on adherence to those requirements. Such conceptual proximity could contribute to the strong statistical association.

The findings are broadly consistent with the theoretical expectation derived from agency theory. Monitoring can reduce information asymmetry by making potentially non-compliant activities easier to identify. In public financial management, timely identification may help oversight officials investigate irregularities and strengthen adherence to established procedures.

However, identifying a potential violation is not equivalent to correcting it. Effective compliance monitoring also requires clear procedures for reviewing alerts, assigning responsibility, documenting decisions and implementing corrective action. AI tools are therefore most useful when integrated into broader internal control and accountability arrangements.

The reduction in the coefficient after including a time trend also deserves attention. Both monitoring adoption and compliance increase over the observation period. This common upward movement may reflect wider changes in digital infrastructure, reporting requirements, management practices or oversight. The trend-adjusted result suggests that the baseline relationship partly reflects these broader changes, although the positive coefficient remains.

A further concern is potential measurement overlap. If the documentation used to score AI adoption also contains evidence of compliance checks, the explanatory and outcome indices may partly reflect the same institutional processes. This could strengthen their observed correlation even when the independent contribution of AI cannot be isolated. Future research should use distinct indicators for system deployment, actual monitoring activity, identified violations and corrective action.

The findings also have implications for responsible technology governance. Automated monitoring systems should be transparent enough for officials and auditors to understand why alerts are generated. Data access should be controlled, system performance should be reviewed, and human officials should retain responsibility for consequential compliance decisions.

Finally, the institutional differences reported in the descriptive analysis suggest that the benefits of AI adoption may depend on implementation capacity. Differences in data quality, staff expertise, information systems and management support could influence whether monitoring technology produces actionable results. These factors warrant explicit examination in subsequent studies.

Limitations. The study has four principal limitations. First, the sample is small (five institutions) and purposively selected for documentary availability, which may favour better-resourced entities and limits generalisability to the wider federal public sector. Second, the study relies on documents that may under-disclose technology use, so the AICM index may understate adoption in institutions that do not publicise it. Third, the scoring is rubric-based and

partly subjective, and the explanatory and outcome indices may partly overlap where the same documents evidence both monitoring and compliance, so the coefficients should be read as index-point associations rather than as physical measures of violations. Fourth, the data do not allow the intermediate steps, alerts raised, cases resolved, recoveries made to be observed, so the study cannot trace the mechanism through which detection is supposed to improve compliance. The study should not be read as evidence that AI adoption caused compliance to improve, nor that the pattern generalises to all federal MDAs.

Conclusion and Recommendations

Conclusion

This study examined the association between documented AI-enabled compliance monitoring and adherence to financial regulations in five Nigerian federal institutions over the period 2015–2024. Using a balanced panel of 50 institution-year observations and a composite-index measurement strategy, the analysis finds a positive and statistically significant association in every specification estimated. The pooled and fixed-effects models produce coefficients of 0.719 and 0.742 respectively (Table 2), and the association remains positive and significant when a linear time trend is added (0.629), in first differences (0.554) and in the lagged specification (0.657). The consistency of the sign and significance across specifications, together with the within-institution pattern, supports the interpretation that the association is not merely a reflection of stable institutional differences. The null hypothesis of no association (H_o) is therefore rejected in favour of the alternative (H_1).

The conclusion must nevertheless be stated with precision. The coefficients are associations between two documented indices, not causal estimates of the effect of AI on compliance. The shrinkage under trend and differencing shows that part of the raw association reflects common temporal drift, including broader public financial management reforms over the period, and the fixed-effects and lagged results mitigate, but cannot eliminate, concerns about reverse causality. The potential overlap between the explanatory and outcome indices is a further caution. The findings therefore support a conditional and directional conclusion: in the selected institutions, deeper documented adoption of AI-enabled compliance monitoring is associated with better documented regulatory compliance, with the conservative estimate placing the association at roughly 0.55 to 0.65 index points per additional point of adoption. They do not establish that AI adoption caused compliance to improve, nor that the pattern generalises to Nigeria's wider federal public sector.

Recommendations

i. **Policymakers and financial management authorities:** Federal institutions should prioritise digital infrastructure and reliable financial data systems. Monitoring tools are unlikely to perform effectively when records are incomplete, fragmented or inconsistent. Investment in AI-enabled monitoring should be matched by investment in data quality, regulatory clarity, staff capacity and institutional learning.
ii. **Regulators:** Regulatory requirements should be documented in clear, machine-readable formats where feasible. This can facilitate automated checks while allowing officials to review the legal basis for system-

generated alerts. Regulators should also require explainability, documentation and audit trails for models used in compliance monitoring, because AI outputs may be wrong and human review remains essential.

iii. **Accountability and audit authorities:** Public institutions should invest in staff training and procedures for investigating and resolving alerts. The value of monitoring depends not only on the detection of irregularities but also on the timely and documented response to them. Institutions should publish operational indicators, exceptions flagged, cases resolved, compliance rates, so that the effects of adoption can be tracked directly rather than inferred from composite indices.

iv. **Governance and future research:** Institutions should establish governance arrangements for AI-enabled monitoring covering data protection, access controls, model validation, audit trails, human oversight and responsibility for decisions made with technological assistance. Four directions follow directly from the limitations of this study. First, larger samples of public institutions and independently validated measures would strengthen inference. Second, transaction-level data on monitoring frequency, alert accuracy, confirmed violations and corrective action would allow detection and correction to be observed as separate steps rather than combined in a composite index. Third, research should examine user acceptance, whether staff find monitoring tools useful and reliable enough to act on, since this mediates whether detection translates into compliance. Fourth, causal designs, staggered roll-outs across ministries, departments and agencies, or natural experiments in adoption timing, would allow the association documented here to be tested as a causal effect.

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