

Digital Financial Reporting Technologies and Financial Reporting Quality of Listed Manufacturing Firms in Nigeria: Evidence from Cloud Accounting, Real-Time Reporting and Artificial Intelligence Integration

Geoffrey Okon Charles, Eno G. Ukpong PhD, Uwakmfonabasi J. Simeon, Patrick E. Akinninyi

<https://doi.org/10.56201/jafm.vol.12.no10.2026.p137.152>

Abstract

The rapid digitalisation of accounting functions has altered the way listed manufacturing firms in Nigeria capture transactions, process financial information and prepare corporate reports. While accounting automation is generally expected to strengthen reporting quality, the benefits of individual technologies may differ according to their depth of adoption, integration and organisational context. This study focuses specifically on three emerging dimensions of digital financial reporting technology—cloud accounting adoption, real-time financial reporting capability, and artificial intelligence and analytics integration—and examines their expected relationship with financial reporting quality among listed manufacturing firms in Nigeria. Financial reporting quality is operationalised through discretionary accruals, with lower discretionary accruals interpreted as evidence of higher reporting quality. The study is framed by agency theory and signalling theory. An ex post facto panel research design is proposed for the 2015–2024 period, using information obtained from published annual reports and audited financial statements of sampled listed manufacturing firms. The empirical model specifies discretionary accruals as a function of cloud accounting adoption, real-time financial reporting capability, artificial intelligence and analytics integration, and firm size. The Modified Jones Model provides the basis for estimating discretionary accruals. Existing evidence from the underlying broader accounting-automation study indicates negative associations for the three retained technology dimensions, with real-time financial reporting reaching conventional statistical significance in the original seven-variable specification, while cloud accounting and artificial intelligence/analytics did not reach the 5 percent threshold. However, those coefficients were estimated in the original seven-variable model and should not be reported as the final coefficients of the present reduced model until the reduced specification is re-estimated. The article therefore provides a complete publication-oriented framework while maintaining this empirical integrity. The study is expected to contribute to the Nigerian accounting-technology literature by isolating three increasingly important digital reporting capabilities and showing why adoption depth, system integration and organisational readiness matter for reporting quality.

Keywords: cloud accounting; real-time financial reporting; artificial intelligence; analytics; financial reporting quality; discretionary accruals; manufacturing firms; Nigeria; accounting technology.

1. Introduction

Financial reporting is central to the functioning of modern capital markets because it provides investors, creditors, regulators, managers and other stakeholders with information for evaluating corporate performance and making economic decisions. The usefulness of financial reporting, however, depends not only on the accounting standards applied but also on the systems through which transactions are captured, processed, reviewed and converted into financial information. As organisations move from predominantly manual accounting processes toward integrated digital environments, technology has increasingly become part of the financial reporting architecture rather than merely a support tool. The digital transformation of accounting has progressed from basic computerised bookkeeping to enterprise-wide information systems, cloud platforms, continuous reporting environments, machine-learning applications and advanced analytics. This transformation creates opportunities for faster transaction processing, stronger audit trails, automated reconciliations, improved exception detection and more timely access to accounting information. At the same time, technology does not automatically guarantee high-quality reporting. Poor implementation, weak controls, unreliable connectivity, cybersecurity risks, inadequate staff competencies, fragmented systems and inappropriate managerial overrides may reduce or even negate the expected benefits of digitalisation. For listed manufacturing firms, the issue is particularly important. Manufacturing operations generate large volumes of transactions involving purchases, inventories, production costs, sales, receivables, payables, payroll, fixed assets and financing activities. The financial reporting process therefore depends on the ability of accounting systems to integrate operational information with financial records. Where systems are fragmented or heavily dependent on manual intervention, errors and delays can arise and managers may have greater opportunities to exercise discretion over estimates, timing and classification. Digital reporting technologies may reduce these opportunities by increasing transaction visibility and standardising processing procedures. The present study narrows the broader accounting-automation perspective to three technologies that have become especially relevant to contemporary financial reporting. The first is cloud accounting adoption (CAA), which refers to the use of internet-based accounting platforms for storing, processing and accessing accounting information. The second is real-time financial reporting capability (RTFRC), referring to the ability of an accounting environment to generate and provide financial information immediately or within a very short interval after transactions occur. The third is artificial intelligence and analytics integration (AIAI), referring to the incorporation of AI, machine learning and advanced analytics into accounting processes for classification, anomaly detection, prediction, monitoring and decision support. The dependent variable is financial reporting quality (FRQ), measured through discretionary accruals (DACC). The use of discretionary accruals is consistent with the earnings-quality literature, where managerial discretion in accrual estimation is treated as one observable manifestation of potential earnings management. Lower discretionary accruals are interpreted as higher reporting quality, subject to the acknowledged limitations of accrual-based proxies (Dechow, Sloan, & Sweeney, 1995; Dechow, Ge, & Schrand, 2010).

The study is motivated by a gap in the existing evidence. Much of the Nigerian literature has examined accounting technology through broad adoption measures, survey-based perceptions, banking-sector samples or qualitative characteristics of reporting. Fewer studies isolate cloud accounting, real-time reporting and AI/analytics simultaneously and relate them to an objective accrual-based proxy of reporting quality among listed manufacturing firms. The present study responds to this gap by focusing on the three retained technology dimensions within a panel-data framework.

1.1 Statement of the Problem

Despite continuing investments in accounting software and digital infrastructure, concerns about the credibility, timeliness and transparency of corporate financial reporting remain. The availability of technology does not necessarily imply that financial reporting processes are fully integrated or that managerial discretion has been effectively constrained. Manufacturing firms may adopt digital tools for selected functions while retaining manual workarounds in critical reporting processes. Consequently, the effect of digital reporting technology on reporting quality may depend more on the depth and integration of adoption than on the mere presence of a technology. Cloud accounting illustrates this problem. Cloud platforms can improve accessibility, data integration and collaboration, but their effect on reporting quality may be limited when firms use them only for peripheral functions, when core accounting remains on-premise, or when concerns about cybersecurity, data sovereignty and internet reliability restrict the scope of adoption. A similar issue arises with artificial intelligence. AI can identify unusual transactions and support predictive analysis, yet its contribution depends on data quality, system integration, staff competence and appropriate human oversight. Real-time financial reporting presents a different but related challenge. Continuous access to financial information can reduce the reporting delay and narrow the period-end window within which managers might manipulate the timing of transactions. However, real-time reporting can also produce preliminary information that requires later adjustment when transactions involve estimates or judgement. The relevant question is therefore not simply whether firms have digital systems, but whether the capability is sufficiently mature to improve reporting quality. These issues create an empirical problem for Nigerian manufacturing firms. Existing evidence does not provide a sufficiently focused understanding of whether cloud accounting, real-time reporting and AI/analytics integration are associated with lower discretionary accruals when considered together. This study therefore examines the relationship between these three digital reporting technologies and financial reporting quality among listed manufacturing firms in Nigeria.

1.2 Objectives of the Study

The main objective is to examine the effect of digital financial reporting technologies on the financial reporting quality of listed manufacturing firms in Nigeria. Specifically, the study seeks to:

1. Examine the effect of cloud accounting adoption on discretionary accruals of listed manufacturing firms in Nigeria.
2. Assess the effect of real-time financial reporting capability on discretionary accruals of listed manufacturing firms in Nigeria.
3. Determine the effect of artificial intelligence and analytics integration on discretionary accruals of listed manufacturing firms in Nigeria.

1.3 Research Questions

1. What effect does cloud accounting adoption have on discretionary accruals of listed manufacturing firms in Nigeria?
2. What effect does real-time financial reporting capability have on discretionary accruals of listed manufacturing firms in Nigeria?
3. What effect does artificial intelligence and analytics integration have on discretionary accruals of listed manufacturing firms in Nigeria?

1.4 Research Hypotheses

H01: Cloud accounting adoption has no significant effect on discretionary accruals of listed manufacturing firms in Nigeria.

H02: Real-time financial reporting capability has no significant effect on discretionary accruals of listed manufacturing firms in Nigeria.

H03: Artificial intelligence and analytics integration has no significant effect on discretionary accruals of listed manufacturing firms in Nigeria.

1.5 Significance of the Study

The study is relevant to management, investors, regulators, accountants and auditors, technology providers, policymakers and researchers. For management, the findings can assist in deciding whether investment should be directed toward broad technology acquisition or deeper integration of particular digital capabilities. Investors may use evidence about technology-enabled reporting environments when assessing the reliability of reported performance. Regulators may obtain evidence relevant to digital reporting expectations, technology risk and continuous monitoring. Accountants and auditors can use the findings in evaluating system-generated evidence, audit trails and areas of residual managerial discretion. Researchers may use the study as a basis for extending the literature on digital accounting transformation in emerging markets.

The study is also important because it distinguishes adoption from effectiveness. A firm may technically use a cloud platform without integrating it with all material accounting processes; similarly, an organisation may describe its reporting system as real-time while still depending on substantial end-of-period manual adjustments. By examining technology dimensions individually, the study provides a more informative view of digital reporting maturity.

1.6 Scope of the Study

The study focuses on listed manufacturing firms in Nigeria. The content scope is restricted to cloud accounting adoption, real-time financial reporting capability and artificial intelligence and analytics integration as explanatory variables, while financial reporting quality is proxied by discretionary accruals. Firm size is included as a control variable. The proposed time scope is 2015–2024, a ten-year period that captures increasing digitalisation of accounting functions and the growing relevance of cloud and AI technologies in the Nigerian business environment. The study is geographically limited to Nigeria and uses firm-year observations derived from published corporate reports and related publicly available information.

1.7 Operational Definition of Terms

Financial reporting quality: The degree to which financial statements provide reliable, relevant, timely and faithfully representative information. In this study it is proxied by discretionary accruals.

Discretionary accruals: The estimated portion of accruals associated with managerial discretion. Lower discretionary accruals are interpreted as higher financial reporting quality.

Cloud accounting adoption: The use of internet-based accounting software and platforms for storing, processing and accessing accounting information remotely.

Real-time financial reporting capability: The ability of an accounting system to generate and provide financial information immediately or within a very short period after transactions occur.

Artificial intelligence and analytics integration: The incorporation of AI, machine learning and data analytics applications into accounting processes for classification, anomaly detection, forecasting, monitoring and reporting support.

Firm size: The scale of the firm, measured in this study by the natural logarithm of total assets.

2. Review of Related Literature

2.1 Conceptual Review

2.1.1 Digital Financial Reporting Technologies

Digital financial reporting technologies refer to digital systems and intelligent applications that support the capture, processing, integration, analysis and communication of financial information. They extend beyond conventional computerised bookkeeping because they increasingly connect transaction processing with operational systems, databases, analytics engines and reporting interfaces. The literature on digitisation suggests that accounting work is being reshaped by internet technologies, big data and automation (Bhimani & Willcocks, 2014; Moll & Yigitbasioglu, 2019). The potential reporting-quality benefit arises through several mechanisms. First, automated systems can reduce repetitive manual entry and associated errors. Second, integrated systems can create consistent data trails across operational and financial processes. Third, continuous monitoring can make unusual transactions more visible. Fourth, digital audit trails can increase the traceability of accounting adjustments. Finally, advanced analytics can allow accountants and auditors to examine large transaction populations rather than relying solely on samples or periodic reviews (Vasarhelyi, Kogan, & Tuttle, 2015).

2.1.2 Cloud Accounting Adoption

Cloud accounting involves delivering accounting applications and data-processing capabilities through internet-based infrastructure. Unlike traditional on-premise systems, cloud environments allow authorised users to access accounting information from different locations and can facilitate automatic software updates, centralised data storage and integration with other applications. Cloud adoption can therefore support financial reporting by reducing information fragmentation and improving the accessibility of current accounting records.

The expected relationship with discretionary accruals is negative. When transactions and supporting information are centrally available and processing is standardised, opportunities for undocumented adjustments and delayed recognition may be reduced. However, the strength of the relationship depends on actual adoption depth. A firm that uses a cloud application for selected functions while maintaining separate legacy systems for core accounting may not experience the same reporting-quality benefits as a fully integrated user.

Evidence from Nigeria is emerging. Recent studies of Nigerian financial institutions and listed firms generally report positive associations between cloud accounting and reporting-quality attributes, although results differ according to the specific dimension of cloud adoption and the proxy used for reporting quality. This variation reinforces the need for firm-level evidence using an objective accrual-based measure rather than relying exclusively on perceived qualitative characteristics.

2.1.3 Real-Time Financial Reporting Capability

Real-time reporting capability refers to the capacity to produce financial information continuously or almost immediately after transactions occur. It represents a movement away from periodic reporting cycles in which information is accumulated and adjusted during a close process. In a

manufacturing environment, real-time integration can connect sales, inventory, production, procurement and accounting information so that financial consequences become visible closer to the point of transaction.

The theoretical mechanism is straightforward. A shorter information cycle reduces the time available for managers to delay, accelerate or reclassify transactions for period-end presentation purposes. Real-time reporting may therefore constrain timing-related earnings management. It may also strengthen oversight because unusual entries can be identified before the close rather than weeks after the underlying event.

Nevertheless, real-time reporting does not eliminate judgement. Estimates for impairment, provisions, depreciation, inventory valuation and other accrual-related items may still require professional judgement and later revision. Thus, real-time capability should be understood as a mechanism for reducing certain forms of discretion rather than as a complete substitute for accounting judgement.

2.1.4 Artificial Intelligence and Analytics Integration

Artificial intelligence and analytics integration represents a more advanced stage of accounting digitalisation. AI systems can classify transactions, identify anomalies, detect unusual patterns, support forecasting and assist in continuous monitoring. Analytics can convert large accounting datasets into information for risk assessment and managerial decision-making. Research on AI in accounting and auditing has highlighted its potential to transform professional work and improve the ability to examine large volumes of transactions (Issa, Sun, & Vasarhelyi, 2016; Kokina & Davenport, 2017; Sutton, Holt, & Arnold, 2016). A negative relationship with discretionary accruals is theoretically plausible. An AI-enabled monitoring system can identify transaction patterns that depart from normal behaviour, flag unusual journal entries and increase the probability that opportunistic adjustments will be detected. However, the effect may be weak where firms lack sufficient historical data, technical skills, integration infrastructure or governance mechanisms. AI systems may also reproduce biases in historical data or produce unreliable classifications when their models are poorly designed or inadequately supervised.

2.1.5 Financial Reporting Quality and Discretionary Accruals

Financial reporting quality is multidimensional and may be considered in terms of relevance, faithful representation, comparability, understandability and timeliness. The earnings-quality literature also links reporting quality to the extent to which reported earnings reflect underlying economic performance and are less affected by opportunistic managerial choices (Dechow, Ge, & Schrand, 2010; Schipper & Vincent, 2003). Discretionary accruals are widely used as an empirical proxy for earnings management. The Modified Jones Model developed from the work of Jones (1991) and Dechow, Sloan, and Sweeney (1995) separates total accruals into estimated non-discretionary and discretionary components. A lower absolute discretionary-accrual measure is generally interpreted as indicating less managerial discretion in reported earnings. The proxy is not without limitations, because accrual estimation may reflect legitimate economic judgement as well as manipulation. The study therefore treats discretionary accruals as an empirical proxy rather than a perfect measure of reporting quality.

2.2 Theoretical Framework

2.2.1 Agency Theory

Agency theory explains the relationship between principals and agents where managers control resources on behalf of shareholders (Jensen & Meckling, 1976). Information asymmetry can give managers opportunities to make reporting choices that benefit themselves rather than shareholders. Digital reporting technologies may reduce this information asymmetry by increasing the speed, completeness and traceability of accounting information. Cloud systems can centralise information, real-time reporting can shorten reporting delays, and AI-based monitoring can identify unusual transactions. These mechanisms can increase the probability of detection and reduce the scope for opportunistic reporting choices.

2.2.2 Signalling Theory

Signalling theory suggests that firms can communicate information about their quality and capabilities through observable actions (Spence, 1973). Investment in sophisticated reporting infrastructure may serve as a signal of commitment to transparency and effective governance. Firms that build reliable digital reporting systems may be able to demonstrate stronger information environments to investors, regulators and other stakeholders. However, a technology investment is only a credible signal when it is supported by effective implementation and reliable reporting outcomes.

2.3 Empirical Review

International evidence increasingly links automation and digitalisation with reporting quality. Ashraf (2024), for example, reports evidence that automation can improve financial reporting quality through stronger internal controls. Studies of AI and accounting information systems likewise suggest that AI can improve data accuracy and accounting-system performance when appropriately implemented. Yang and Zhou (2025) report evidence that AI adoption can improve the quality of corporate accounting-information disclosure. Nigerian studies on cloud accounting and digital accounting systems generally suggest beneficial effects, although findings differ according to industry, technology dimension and reporting-quality proxy.

Evidence on real-time reporting is particularly relevant to accrual-based reporting quality. Studies reported in the underlying source research indicate that firms with mature real-time reporting capabilities tend to exhibit lower discretionary accruals, with stronger effects for timing-related accruals. This is consistent with the argument that continuous visibility reduces opportunities for period-end manipulation. At the same time, evidence also indicates that real-time systems may introduce reliability challenges when transactions require estimates that are subsequently revised. AI evidence is more mixed in emerging-market settings. While AI-supported anomaly detection and automated classification may improve accuracy, adoption remains comparatively immature in many firms. The absence of a statistically significant effect in an emerging setting should therefore not necessarily be interpreted as evidence that AI is ineffective. It may instead indicate that adoption has not reached a level of maturity, data quality or organisational integration sufficient to produce measurable reporting outcomes.

Cloud accounting presents a similar issue. Recent Nigerian evidence has generally identified positive effects on reporting characteristics, but adoption levels vary and some firms retain hybrid architectures. Consequently, the present study treats cloud accounting adoption as a substantive explanatory dimension rather than assuming that the mere presence of cloud software automatically improves reporting quality.

2.4 Research Gap

The literature reveals four principal gaps. First, much Nigerian research has concentrated on banking and financial institutions, leaving comparatively less evidence for manufacturing firms. Second, several studies rely on survey perceptions or qualitative characteristics of financial reporting rather than an objective accrual-based proxy. Third, studies frequently investigate individual technologies separately, making it difficult to compare their relative relationships within the same model. Fourth, the rapid development of cloud, real-time and AI technologies means that evidence from earlier periods may not adequately reflect the current digital environment.

This study addresses these gaps by concentrating on listed manufacturing firms, employing discretionary accruals as the dependent proxy, and modelling cloud accounting, real-time reporting and AI/analytics integration jointly while controlling for firm size. The reduced three-variable design also provides a more focused interpretation than a broad seven-dimensional automation index.

2.5 Conceptual Framework

Independent variables	Expected relationship	Dependent variable	Control
Cloud Accounting Adoption (CAA)	Negative	Discretionary Accruals (DACC) / Financial Reporting Quality	Firm Size (FSIZE)
Real-Time Financial Reporting Capability (RTFRC)	Negative	Lower DACC = higher FRQ	
Artificial Intelligence & Analytics Integration (AIAI)	Negative		

Figure 1: Conceptual relationship. Source: Author's conceptualisation (2026).

The framework proposes that stronger adoption of cloud accounting, real-time reporting and AI/analytics should be associated with lower discretionary accruals. Firm size is introduced as a control because larger firms may face greater regulatory scrutiny and may possess more resources to invest in sophisticated accounting systems and controls.

3. Methodology

3.1 Research Design

The study adopts an ex post facto research design. The design is appropriate because the study relies on historical information that already exists in published annual reports and audited financial statements and the researcher does not manipulate the explanatory variables. Panel-data techniques are suitable because observations are available across firms and years, allowing both cross-sectional and time-series variation to be considered.

3.2 Population and Sample

The intended population consists of manufacturing firms listed on the Nigerian Exchange Group during the study period. The underlying source study indicates a final analytical sample of 16 firms and 160 firm-year observations for 2015–2024. However, another section of the source material refers to 17 firms. Because 160 observations over ten years correspond to 16 firms, the 16-firm

figure is internally consistent with the stated observation count, but the final firm list should be verified against the underlying dataset and annual reports before submission. This issue is explicitly retained here rather than silently corrected.

A purposive sampling approach is appropriate where firms must have sufficiently complete annual-report information across the study period. Firms with extensive missing data or inconsistent reporting records would ordinarily be excluded. The final manuscript should state the exact names of the sampled firms and the precise number of firm-year observations after the underlying data have been reconciled.

3.3 Sources and Method of Data Collection

The study relies primarily on secondary data. Financial statement information is obtained from published annual reports and audited financial statements of sampled listed manufacturing firms. Information relevant to technology adoption is extracted from annual reports, corporate disclosures and other verifiable public disclosures where available. The use of audited corporate reports is intended to improve consistency and reduce dependence on subjective responses.

3.4 Measurement of Variables

Variable	Symbol	Measurement
Discretionary accruals / FRQ	DACC	Estimated using the Modified Jones Model; lower absolute DACC indicates higher reporting quality.
Cloud accounting adoption	CAA	Index reflecting the extent of adoption/use of internet-based accounting platforms.
Real-time financial reporting capability	RTFRC	Index reflecting the firm's capacity to generate financial information immediately or near-immediately after transactions.
AI and analytics integration	AIAI	Index reflecting incorporation of AI, machine learning and analytics into accounting/reporting processes.
Firm size	FSIZE	Natural logarithm of total assets.

3.5 Measurement of Discretionary Accruals

The Modified Jones Model is used to estimate discretionary accruals. The procedure begins with total accruals, which are separated into estimated non-discretionary accruals and discretionary accruals. Following Jones (1991) and Dechow, Sloan, and Sweeney (1995), the model incorporates changes in revenue, property, plant and equipment, and the adjustment for changes in receivables in estimating expected accrual behaviour. The discretionary component is the residual from the accrual model.

A general form of the estimation is expressed as:

$TA_{it} / A_{i,t-1} = \alpha_1(1/A_{i,t-1}) + \alpha_2[(\Delta REV_{it} - \Delta REC_{it})/A_{i,t-1}] + \alpha_3(PPE_{it}/A_{i,t-1}) + \varepsilon_{it}$
where TA is total accruals, A is lagged total assets, ΔREV is the change in revenue, ΔREC is the change in receivables, and PPE is property, plant and equipment. The estimated residual ε represents discretionary accruals. Absolute discretionary accruals may be used when the focus is the magnitude of reporting discretion rather than its direction.

Because the interpretation of the dependent variable is inverse, a negative coefficient on a technology variable indicates that greater adoption is associated with lower discretionary accruals and therefore potentially higher financial reporting quality.

3.6 Model Specification

The reduced empirical model is specified as follows:

$$DACC_{it} = \beta_0 + \beta_1 CAA_{it} + \beta_2 RTFRC_{it} + \beta_3 AIAI_{it} + \beta_4 FSIZE_{it} + \varepsilon_{it}$$

Where: DACC = discretionary accruals; CAA = cloud accounting adoption; RTFRC = real-time financial reporting capability; AIAI = artificial intelligence and analytics integration; FSIZE = firm size; β_0 = intercept; β_1 – β_4 = regression coefficients; ε = error term; i = firm; t = year.

The expected signs for β_1 , β_2 and β_3 are negative. The expected sign for firm size is also negative based on the argument that larger firms face greater monitoring and possess greater resources for reporting systems. The exact empirical signs and statistical significance of the reduced model must, however, be determined by re-estimating the model with the verified underlying data.

3.7 Estimation Procedure

The analysis should begin with descriptive statistics covering the mean, median, standard deviation, minimum and maximum values of each variable. Correlation analysis can then be used to assess the direction and preliminary strength of relationships. Multicollinearity should be evaluated using variance inflation factors or an equivalent diagnostic. Panel regression should subsequently be estimated using pooled ordinary least squares, fixed effects and random effects as appropriate. Model-selection procedures, including the Hausman specification test, should guide the choice between fixed and random effects. Robust standard errors should be considered where heteroskedasticity or within-panel dependence is detected.

The decision rule for each hypothesis is based on the selected significance level, ordinarily 5 percent. A p-value below 0.05 leads to rejection of the corresponding null hypothesis, while a p-value greater than 0.05 leads to failure to reject it. Statistical significance should be interpreted alongside coefficient direction and economic meaning.

4. Empirical Evidence and Results Status

An important distinction is required between the results of the underlying seven-variable source study and the results of the present reduced three-variable article. The source study estimated a broader model containing seven accounting-automation dimensions. Its reported random-effects coefficients for the three variables retained in this article were: CAA = -0.012345 ($p = 0.0709$), RTFRC = -0.016789 ($p = 0.0257$), AIAI = -0.013456 ($p = 0.0558$), and FSIZE = -0.007890 ($p = 0.0125$). The broader model reported R^2 of approximately 0.688 and adjusted R^2 of approximately 0.671, while the Hausman statistic was reported as 10.234 with 8 degrees of freedom and $p = 0.2487$. These figures are useful as source-study evidence and as a basis for understanding the broader research context. They must not, however, be presented as the final results of the present article because removing four explanatory variables changes the estimated partial relationships among the retained variables. The reduced model must be re-estimated using the verified

underlying dataset. This distinction is essential for methodological integrity and publication quality.

4.1 Interpretation of the Source-Study Evidence for the Retained Variables

4.1.1 Cloud Accounting Adoption and Discretionary Accruals

In the broader source model, cloud accounting adoption has a negative coefficient of -0.012345 with a p-value of 0.0709. The negative sign is consistent with the expectation that cloud adoption may reduce discretionary accruals, but the relationship is not statistically significant at the conventional 5 percent level in that original specification. The result suggests that the direction of the relationship is potentially beneficial, but the available evidence from the original model is insufficient to conclude that cloud accounting adoption independently reduces discretionary accruals at the 5 percent threshold. A plausible explanation is adoption depth. A firm may operate a cloud accounting application without fully integrating production, inventory, sales, procurement and financial reporting systems. In such circumstances, manual reconciliations and adjustments may continue to create reporting discretion. Concerns over cybersecurity, data sovereignty and internet reliability may also encourage hybrid architectures. The implication is that the quality effect of cloud accounting may depend on whether the technology replaces fragmented processes or merely adds another digital layer.

4.1.2 Real-Time Financial Reporting Capability and Discretionary Accruals

The source study reports a coefficient of -0.016789 and a p-value of 0.0257 for RTFRC. In the original seven-variable specification, this represents a negative and statistically significant relationship at the 5 percent level. The interpretation is that stronger real-time reporting capability is associated with lower discretionary accruals. The result is consistent with the argument that continuous information visibility reduces opportunities for period-end timing manipulation.

Manufacturing firms may benefit especially because sales, inventory and production events occur continuously. When these events feed accounting systems promptly, the opportunity to postpone or accelerate recognition around reporting cut-offs may be reduced. However, the benefit depends on system reliability and on the quality of estimates used in real-time reporting. The reduced model should be re-estimated before the finding is stated as the definitive result of this article.

4.1.3 AI and Analytics Integration and Discretionary Accruals

The source study reports a coefficient of -0.013456 with a p-value of 0.0558 for AIAI. The coefficient is negative and therefore directionally consistent with improved reporting quality, but the p-value is slightly above the conventional 5 percent threshold. The evidence therefore does not justify rejecting the null hypothesis at 5 percent in the original model. The near-significant result is nevertheless informative. AI and analytics may have substantial potential, but the technology requires clean data, adequate computational infrastructure, appropriate model governance and staff who can interpret system outputs. In emerging-market firms where AI adoption is still developing, limited exposure may make the statistical effect difficult to detect. Future evidence may therefore change as firms move from experimentation to integrated, enterprise-wide AI use.

4.1.4 Firm Size and Discretionary Accruals

Firm size has a source-study coefficient of -0.007890 and a p-value of 0.0125, indicating a negative and statistically significant relationship in the original broader model. Larger firms may have stronger monitoring environments, greater exposure to regulators and capital-market

scrutiny, and more resources for sophisticated accounting systems and internal controls. Again, this coefficient belongs to the original model and should not be copied into the reduced model without re-estimation.

4.2 Summary of Source-Study Statistical Evidence

Variable	Source-study coefficient	p-value	5% conclusion in original model
CAA	-0.012345	0.0709	Not significant
RTFRC	-0.016789	0.0257	Significant
AIAI	-0.013456	0.0558	Not significant
FSIZE	-0.007890	0.0125	Significant

Note: These values are from the original seven-variable model in the underlying source study. They are not the final coefficients of the present reduced three-variable model.

5. Discussion of Findings

The central argument emerging from the evidence is that digital reporting technologies can influence reporting quality, but their effects are not necessarily uniform. Real-time reporting appears to have the clearest empirical association in the underlying broader model, while cloud accounting and AI/analytics exhibit negative but statistically weaker relationships. This pattern is theoretically plausible because real-time reporting directly affects the timing and visibility of transactions, whereas cloud and AI technologies may require broader organisational integration before their reporting-quality effects become observable.

The cloud-accounting finding is consistent with the idea that technology adoption is not binary in practical terms. Firms may subscribe to cloud applications while retaining substantial on-premise processes. Consequently, the reporting-quality benefit may be conditional on integration. This interpretation is consistent with recent Nigerian literature reporting generally positive but context-dependent relationships between cloud accounting and reporting quality.

The real-time reporting result is consistent with agency theory because more immediate information reduces information asymmetry between managers and external stakeholders. It is also consistent with the monitoring mechanism implied by signalling theory: a reporting environment that produces timely and traceable information may signal stronger commitment to transparency. The effect is particularly relevant to manufacturing firms because the timing of inventory, sales and expense transactions can materially influence reported performance.

The AI/analytics result demonstrates why technological sophistication should not be confused with technological effectiveness. AI can be powerful, but its usefulness depends on data quality, system architecture, governance and human oversight. A poorly integrated AI system may add complexity without materially changing the underlying reporting process. The near-significant negative association in the source model suggests potential value but also indicates that stronger evidence is needed.

6. Conclusion

This article examined the relationship between three digital financial reporting technologies—cloud accounting adoption, real-time financial reporting capability, and artificial intelligence and analytics integration—and financial reporting quality among listed manufacturing firms in Nigeria. The study conceptualises reporting quality through discretionary accruals and argues that digital technologies can improve reporting quality by reducing manual intervention, increasing

transaction visibility, strengthening monitoring and limiting opportunities for opportunistic reporting choices.

The evidence from the underlying broader accounting-automation model indicates that the three retained variables have negative coefficients, suggesting a direction consistent with lower discretionary accruals. Real-time financial reporting capability was statistically significant in the original model, while cloud accounting and AI/analytics were not significant at the conventional 5 percent level. These results should be interpreted as source-study evidence rather than final estimates for the present reduced model. A final publication manuscript should replace this section's source-study evidence with the coefficients obtained after re-estimating the reduced specification from the verified dataset.

The broader conclusion is that digitalisation can support higher-quality financial reporting, but the effectiveness of a technology depends on implementation maturity. Technology acquisition alone is insufficient. Firms need integrated systems, reliable data, strong controls, competent personnel and governance structures that ensure automated outputs are accurate and appropriately reviewed.

7. Recommendations

1. Listed manufacturing firms should prioritise integration rather than simple acquisition of accounting technologies. Cloud applications, operational systems and financial reporting systems should communicate through reliable interfaces so that manual workarounds are reduced.
2. Firms should strengthen real-time reporting capabilities, particularly for high-volume transactions involving sales, inventory, production and receivables. Continuous reporting should be supported by reconciliation controls that distinguish preliminary information from final accounting estimates.
3. Management should invest in AI and analytics only alongside data governance, cybersecurity, staff training and model oversight. AI outputs should remain subject to appropriate professional review.
4. Regulators and professional bodies should encourage digital reporting maturity through guidance on system controls, audit trails, data governance and technology-related financial reporting risks.
5. Auditors should increase their understanding of automated accounting environments and incorporate system-generated evidence, continuous monitoring and technology-related control risks into audit planning.
6. Investors and other users of financial statements should consider the quality of firms' reporting infrastructure as part of their broader assessment of governance and information risk.
7. Future studies should use verified firm-level technology indices and re-estimate reduced specifications when variables are removed from a broader model rather than mechanically transferring coefficients from the original specification.

8. Contribution to Knowledge

The study contributes to knowledge in several ways. First, it narrows the broad accounting-automation construct to three contemporary digital reporting technologies, allowing clearer interpretation of their individual relationships with reporting quality. Second, it focuses on Nigerian listed manufacturing firms, a setting in which digital reporting evidence remains less developed than evidence from banking and developed capital markets. Third, it employs discretionary accruals rather than relying exclusively on perceptions of reporting quality. Fourth, it emphasises adoption depth and implementation maturity as important explanations for why

technology may produce different reporting outcomes across firms. Finally, the study identifies the need to re-estimate reduced models when research questions are narrowed, thereby reinforcing methodological transparency in derivative research.

9. Limitations and Directions for Future Research

The study is limited by its focus on listed manufacturing firms and therefore may not generalise to unlisted firms or other sectors. Technology adoption measures derived from public disclosures may also understate capabilities that firms do not disclose. The discretionary-accrual proxy has known measurement limitations and should ideally be complemented with alternative reporting-quality measures. Future research can incorporate earnings restatements, reporting timeliness, internal-control weaknesses, audit quality and textual measures of disclosure quality. Researchers may also investigate whether corporate governance, audit committee effectiveness, cybersecurity maturity or digital skills moderate the technology–reporting-quality relationship.

Future work should also distinguish between implementation stages. Comparing firms at basic, intermediate and advanced levels of cloud, real-time and AI adoption may reveal nonlinear effects that are not visible in a simple continuous specification. In addition, future studies could examine whether AI and cloud technologies become more strongly associated with reporting quality as Nigerian firms develop more mature digital infrastructures.

10. Publication and Empirical Integrity Note

This document has deliberately preserved the distinction between the original source study and the present article. The original source study contains a seven-variable accounting-automation model. The present article retains only cloud accounting adoption, real-time financial reporting capability and artificial intelligence and analytics integration, with firm size as a control. Because regression coefficients depend on the complete specification, the original seven-variable coefficients cannot validly be presented as estimates from the new reduced model. The final empirical tables, hypothesis decisions, model-fit statistics and diagnostic tests should therefore be updated after the reduced model is re-estimated using the verified underlying dataset.

The source material also contains an internal sample-description inconsistency: one section reports 16 firms and 160 observations, while another refers to 17 firms. The 16-firm figure is arithmetically consistent with 160 firm-years over ten years, but the actual firm list and dataset should be checked before submission. This document does not silently resolve that inconsistency because doing so without inspecting the underlying data could create a factual error.

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