
ARTIFICIAL INTELLIGENCE AND FINANCIAL REPORTING ACCURACY: A NARRATIVE REVIEW

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2. ABSTRACT

This article examines how artificial intelligence may affect financial reporting accuracy, anomaly screening and reporting efficiency. A narrative review synthesizes recent accounting research, evidence from selected Zambian firms and authoritative risk-management guidance. The literature identifies potential benefits from transaction classification, data extraction, reconciliation, exception analysis and reporting assistance. Published findings include associations between AI use and perceived reporting accuracy, and field evidence relating generative AI to reporting quality and closing speed. These results do not establish that every AI application improves accuracy or that observational relationships are causal. Anomaly alerts support investigation but do not prove fraud. Benefits depend on source-data quality, appropriate accounting logic, internal controls, system validation and professional review. Costs, skills gaps, infrastructure, security, privacy, explainability and excessive reliance on automated outputs constrain adoption. The article proposes phased implementation with clear responsibilities, data controls, human approval and monitoring of both accuracy and efficiency. AI is best treated as support for accountable accounting judgment. Future evaluations should compare independently verified reporting errors and processing outcomes, rather than relying solely on adoption levels or user perceptions.

3. KEYWORDS: Artificial intelligence; financial reporting accuracy; Anomaly detection; Data governance; Human oversight; Zambia.

4. INTRODUCTION

Financial reporting is a central component of corporate accountability because it provides information used by managers, investors, lenders, regulators, employees and other stakeholders to evaluate an organization's financial position and performance. The usefulness of financial reports depends heavily on the quality of the underlying accounting information. Accuracy is particularly important because errors, omissions, inappropriate classifications and fraudulent entries can distort reported performance and lead users to make poor decisions. As accounting systems have become increasingly digital, organizations have accumulated large volumes of structured and unstructured financial data that must be processed within increasingly demanding reporting deadlines.

Artificial Intelligence (AI) has emerged as one of the technologies capable of transforming this environment. AI refers broadly to computational systems that can perform tasks associated with human intelligence, including pattern recognition, prediction, classification, natural-language processing and decision support. In accounting, AI can be embedded in enterprise resource planning systems, accounting information systems, reconciliation tools, audit analytics and reporting platforms. Its applications range from automated transaction classification and data extraction to anomaly detection and assistance with financial-statement disclosures.

Automation can reduce routine data-entry and reconciliation work. Choi and Xie (2026) report field associations between generative AI use, reporting quality and closing speed, alongside experimental evidence on human review. Johri (2025) reports positive relationships involving AI, accounting-system quality, internal controls and reporting accuracy. Study setting and design remain important when applying these findings.

AI is also relevant to financial control and fraud-risk management. Machine-learning and data-analytics techniques can examine large transaction populations and identify patterns that differ from expected behavior. Such systems may flag duplicate payments, unusual journal entries, abnormal transaction timing, unexpected account relationships or other indicators requiring investigation. However, anomaly detection should not be equated with proof of fraud. A transaction can be unusual without being fraudulent, while a sophisticated fraudulent transaction can be designed to appear normal. Consequently, professional investigation remains necessary.

The reporting environment is also changing because AI can reduce the time required to prepare, reconcile and analyze financial information. The Financial Reporting Council (FRC, 2026) reports that AI use in corporate reporting is increasing but remains cautious and

uneven, with adoption concentrated on lower-risk, task-specific activities such as data extraction, consolidation, reconciliation and anomaly identification. Recent field evidence likewise associates generative AI adoption with faster month-end closing and improved reporting quality (Choi & Xie, 2026).

AI adoption introduces data, model and governance risks. The Financial Reporting Council (2026) identifies trust and data quality among constraints on corporate-reporting use. The National Institute of Standards and Technology (NIST, 2023) provides a risk-management framework covering reliable, secure, transparent and accountable AI.

Mwachikoka et al. (2026) report a positive relationship between AI adoption and perceived reporting accuracy among 60 respondents from selected firms in Livingstone, Zambia. Their reported correlation is $r = 0.700$ and the simple-model R-squared is 0.491. These observational findings establish local relevance but do not demonstrate that AI caused the improvement.

Research Problem

Traditional financial reporting processes can involve extensive manual data entry, reconciliation, classification and review. Although accounting information systems have reduced many routine errors, human involvement remains substantial. Errors may arise from fatigue, inadequate review, incorrect coding, duplicated entries, incomplete reconciliations or inconsistent application of accounting procedures. At the same time, organizations face growing volumes of financial data and pressure to produce timely information. These conditions create a need for technologies capable of increasing processing capacity without weakening reliability.

AI offers a possible response, but its adoption does not automatically guarantee accurate financial reporting. Poor-quality source data can produce poor AI outputs; biased or poorly designed models can misclassify transactions; and users may over-rely on systems that are difficult to explain. There is therefore a need for an integrated examination of AI's positive and negative effects on financial reporting accuracy, including its role in error reduction, anomaly and fraud detection, timeliness and organizational efficiency.

Objectives of the Study

The study was guided by the following objectives:

- To evaluate the impact of AI on the accuracy of financial reports by reducing human errors and enhancing data processing capabilities.

- To assess the effectiveness of AI in detecting anomalies and fraudulent practices in financial statements.
- To examine the influence of AI on the timeliness and efficiency of financial reporting processes.
- To identify the challenges and limitations associated with AI adoption in financial reporting.
- To propose recommendations for maximizing AI's positive impact on financial reporting accuracy.

Significance of the Study

The study is relevant to accounting professionals, auditors, finance managers, regulators, technology providers, researchers and organizations considering AI adoption. For accounting professionals, it highlights the changing balance between automation and professional judgment. For managers, it identifies conditions required to obtain reliable benefits from AI investments. For auditors and regulators, it emphasizes the importance of explainability, data governance, cyber security and human accountability. For organizations in developing economies such as Zambia, the discussion also highlights the need to consider infrastructure, skills and implementation costs when adopting AI-enabled reporting systems.

5. MATERIALS AND METHODS

This article uses a desk-based narrative review of recent accounting research and official institutional guidance. The cited literature was organized around reporting accuracy, anomaly screening, reporting timeliness, adoption risks and responsible implementation. Publisher and institutional records were checked through 5 October 2026. Particular attention was given to study design, outcome definition and the distinction between measured performance and respondent perceptions.

This thematic synthesis is non-exhaustive. No search register, independent screening process, formal quality score or pooled effect estimate is reported. The article contains no new survey, experiment or interview findings. Comparisons retain the original settings and limitations of the underlying studies, including the limits of observational evidence for causal inference.

Conceptual orientation

The article conceptualizes AI adoption as the independent factor and financial reporting accuracy as the principal dependent outcome. AI adoption includes automated data processing, machine learning, natural-language processing, automated reconciliation,

anomaly detection and generative-AI assistance. Financial reporting accuracy is considered in terms of reduced processing errors, consistency, reliable classification, effective reconciliation and improved quality of reported information. Reporting timeliness and fraud/anomaly detection are treated as important supporting dimensions.

Table 1. Proposed AI mechanisms and reporting outcomes. The pathways are conceptual and depend on implementation and controls.

AI-related factor	Mechanism	Expected reporting outcome
Automated data processing	Processes large transaction volumes consistently	Fewer manual processing errors; improved consistency
Machine learning / analytics	Identifies patterns and unusual transactions	Earlier anomaly and fraud-risk detection
Automated reconciliation	Matches records and identifies differences	More complete and accurate reconciliations
Natural-language processing / GenAI	Extracts, summarizes and assists with reporting text	Faster reporting and improved disclosure support
Human oversight and controls	Reviews and validates AI outputs	Reduced risk of inappropriate automated decisions

6. RESULTS AND DISCUSSION

AI and Financial Reporting Accuracy

The literature generally indicates that AI can improve financial reporting accuracy when it is applied to suitable tasks and supported by reliable data and controls. The main mechanism is automation. Routine activities such as transaction classification, data extraction, reconciliation and validation can be performed at scale with consistent rules or learned patterns. This reduces dependence on repetitive manual work and creates additional opportunities for accountants to concentrate on exceptions and professional judgment.

The Livingstone survey reports perceived reporting accuracy rather than an independently audited error rate. The five-dimension model has a reported R-squared of 0.584, with natural-language processing identified as a significant unique predictor (Mwachikoka et al., 2026). This is contextual evidence of association within the selected sample, not a causal estimate or a prediction for all Zambian firms.

International studies also require qualified interpretation. Johri (2025) examines respondents from India and finds relationships involving AI, internal controls and accounting-system quality. Choi and Xie (2026) examine field, survey and experimental evidence. Their findings support human review and indicate that accepting non-consensus AI recommendations can create error risk. Differences in tasks, samples and measures prevent a single universal estimate of accuracy improvement.

The relationship between AI and accuracy can therefore be expressed as conditional rather than automatic. If source data are incomplete or inaccurate, an AI system can process the errors more efficiently without correcting their underlying cause. Similarly, if an algorithm is poorly trained, inappropriate for the accounting context or inadequately monitored, automation may introduce systematic errors. Accuracy therefore depends on the combination of technology, data quality, accounting rules, internal controls and professional judgment.

AI in Anomaly and Fraud Detection

AI can strengthen financial control by examining large volumes of transactions for patterns that may be difficult to identify through manual sampling. Machine-learning models can learn expected transaction behavior and flag observations that differ from established patterns. Analytics can also compare relationships among accounts, vendors, customers, dates, amounts and transaction frequencies. These capabilities make AI particularly useful for continuous monitoring and risk-based investigation.

The risk-management implication is to evaluate exception screening as a controlled process. A useful system must identify relevant unusual transactions, explain the basis of alerts where feasible, and support documented follow-up. Kokina et al. (2025), drawing on auditing field interviews, identify opportunities alongside implementation and reliability challenges. Their evidence should not be read as a measured reduction in fraud incidence.

An important distinction is between anomaly detection and fraud confirmation. Anomaly detection identifies transactions or patterns that warrant attention. Fraud determination requires contextual investigation, evidence and professional judgment. A large unusual payment, for example, may represent legitimate capital expenditure, an emergency procurement or an accounting error rather than fraud. Conversely, a fraudulent transaction may be deliberately structured to resemble normal transactions. Effective systems should therefore route high-risk alerts to qualified personnel rather than automatically label transactions as fraudulent.

AI also creates a new control challenge: adversarial behavior. Once employees or external actors understand how monitoring systems work, they may attempt to avoid detection. This makes model monitoring and periodic updating important. The use of multiple analytical techniques, independent review and changing risk indicators can reduce the likelihood that fraudsters learn to exploit a static detection model.

AI, Timeliness and Efficiency of Financial Reporting

Timeliness is an important quality of financial information because information loses decision value when it becomes available too late. AI can improve timeliness by reducing the time required for data extraction, classification, reconciliation, and analysis and report preparation. Automation can also allow organizations to move from periodic manual checking toward more continuous monitoring.

Choi and Xie (2026) associate generative AI use with faster month-end closing and a shift in accountant effort toward communication and quality assurance. The field relationships require interpretation within their study setting. Faster processing should be assessed together with unresolved errors and the quality of review.

The Financial Reporting Council (2026) describes cautious, human-led corporate-reporting use. Its findings support the need for task-specific adoption and governance rather than a universal reporting-accuracy claim.

However, faster reporting is valuable only when accuracy is maintained. An organization that produces financial reports quickly but with unresolved errors has not achieved a meaningful improvement in reporting quality. AI implementation should therefore be evaluated using a balanced set of measures, such as processing time, reconciliation exceptions, error rates, manual adjustments, quality of audit evidence, unresolved anomalies and reporting-cycle duration.

Challenges and Limitations of AI Adoption

The first challenge is data quality. AI systems depend on the quality, completeness and consistency of the data used for training, operation and validation. In accounting, data may originate from multiple systems with different coding structures and levels of completeness. If master data are inconsistent or transactions are incorrectly captured, AI outputs can reproduce or amplify those weaknesses.

The second challenge is explainability. Some machine-learning models can be difficult for accounting professionals and regulators to interpret. Financial reporting requires accountability: users need to understand why a transaction was classified in a particular way, why an anomaly was flagged and who is responsible for approving the final treatment. An opaque model can therefore create governance difficulties even when its statistical performance appears strong.

Financial systems contain sensitive business and personal data. Access controls, secure interfaces, monitoring and vendor review are therefore central to AI implementation. The

NIST (2023) framework connects these concerns with accountability, reliability and transparency.

Skills gaps and implementation costs can constrain adoption. Accounting professionals need to understand both accounting rules and the limitations of digital outputs. Organizations' should assess the cost of data preparation, infrastructure, system integration, training, validation and ongoing support before deployment.

Excessive reliance on AI can weaken professional review. Choi and Xie (2026) show why confidence information and intervention matter, particularly when recommendations lack consensus. Staff should retain responsibility for checking accounting treatment, exceptions and supporting evidence.

Organizations need documented policies for acceptable use, model changes, review, security and final approval. Trust and governance concerns identified by the Financial Reporting Council (2026) reinforce the value of a controlled implementation process.

Synthesis of Findings by Objective

Table 2. Thematic synthesis and implementation implications.

Objective	Main finding from literature	Implication
1. Accuracy and human errors	AI generally supports more consistent processing, automated reconciliation and reduced repetitive manual work.	Accuracy improves when AI is supported by good data and human validation.
2. Anomalies and fraud	AI and analytics can monitor large transaction populations and identify unusual patterns earlier.	AI strengthens fraud-risk detection but does not replace investigation or professional skepticism.
3. Timeliness and efficiency	Automation and GenAI can reduce processing and month-end closing time.	Organizations can shorten reporting cycles while reallocating staff toward review and analysis.
4. Challenges and limitations	Key barriers include data quality, skills, cost, cyber security, privacy, explainability, bias and over-reliance.	Adoption should be phased and governed rather than technology-led alone.
5. Recommendations	The strongest evidence favors human-AI collaboration, governance, training, data controls and continuous monitoring.	AI should augment professional judgment and be embedded within a strong control environment.

Practical Recommendations

Based on the literature synthesis, the following recommendations are proposed for organizations seeking to maximize the positive effect of AI on financial reporting accuracy:

- Adopt AI gradually, beginning with well-defined, high-volume and relatively rule-based activities such as data extraction, reconciliation, transaction classification and anomaly screening.
- Establish strong data governance. Organizations should define data ownership, validation procedures, access controls, quality checks, retention requirements and audit trails before expanding AI use.
- Maintain human-in-the-loop controls. AI-generated classifications, exceptions and disclosures should be subject to review and approval by appropriately qualified accounting or finance personnel, especially in judgment-intensive areas.
- Develop continuous professional training. Accountants should be trained in AI capabilities, limitations, data interpretation, prompt and system use, cyber security, professional skepticism and validation of automated outputs.
- Create AI governance policies that clearly assign responsibility for model selection, validation, monitoring, changes, documentation, security and final reporting decisions.
- Use AI for continuous anomaly monitoring while preserving independent investigation. Alerts should be risk-ranked and investigated using supporting evidence rather than automatically treated as fraud.
- Regularly validate and test AI systems. Organizations should monitor error rates, false positives, false negatives, model drift, unexpected outputs and changes in data patterns.
- Strengthen cyber security and privacy controls, particularly where AI tools connect to accounting systems, cloud platforms or external vendors.
- Measure AI performance using both efficiency and quality indicators, including reporting-cycle time, reconciliation accuracy, manual adjustments, detected exceptions, unresolved errors and audit findings.
- For organizations in developing economies, including Zambia, align AI investment with infrastructure capacity and organizational readiness. Partnerships, phased implementation and targeted skills development may provide a more sustainable path than large-scale technology deployment without adequate support.

Proposed Implementation Framework

The proposed implementation cycle comprises readiness assessment, use-case selection, data preparation, controlled deployment, outcome monitoring and improvement. This is an author-developed practical sequence informed by the NIST (2023) functions govern, map, measure and manage, rather than a separately validated model.

Before deployment, management should confirm data quality, infrastructure, staff capability and reporting controls. Selected applications should have defined review and approval points. Monitoring should cover accuracy, unresolved anomalies, security and user behaviour. Changes to models, procedures and training should respond to documented findings.

Limitations

The review combines different technologies, countries, tasks and study designs. Perceived reporting accuracy, transaction classification, disclosure quality and verified financial-statement errors are distinct outcomes. The narrative selection cannot establish exhaustive coverage or a pooled causal effect. Rapid changes in AI systems also limit the transfer of findings across tools and time. Future research should specify the system, task, benchmark, error definition and oversight process, and should assess outcomes against independent accounting evidence.

7. CONCLUSION

AI may support financial reporting through controlled automation, reconciliation, exception analysis and reporting assistance. Recent accounting studies and institutional guidance identify both useful applications and material limitations. Zambian survey evidence supports local relevance while retaining the limits of perceived outcomes and observational analysis.

Accurate reporting depends on source records, appropriate accounting rules, internal controls and professional responsibility. Anomaly detection does not establish fraud, and faster processing does not guarantee reliable statements. A narrative synthesis cannot determine the effect of every AI system or substitute for direct validation.

Organizations' should adopt suitable applications in stages, maintain data and security controls, train accounting personnel and review automated outputs. Evaluation should measure both efficiency and independently verified reporting quality. AI can support accounting judgment when responsibility for the final reports remains clearly assigned.

8. ACKNOWLEDGEMENTS

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