JOURNAL OF CONTEMPORARY ISSUES IN ACCOUNTING
Volume 7, Number 1, July 2026, pp. 1 – 16.
ISSN 2814 - 1113
https://journals.unizik.edu.ng/index.php/jocia/index

REENGINEERING CONTEMPORARY ACCOUNTING THOUGHT AND PRACTICE: THE TRANSFORMATIVE ROLE OF ARTIFICIAL INTELLIGENCE IN FINANCIAL ACCOUNTING

Samuel Sejjaaka[1] **Raphael Kiba**[2]
MAT Abacus Business School, Uganda
Correspondence: info@matabacus.ac.ug

ABSTRACT

Accounting practice has always evolved slowly. For most of its history, the core work of the profession (recording transactions, summarizing them, and preparing financial statements as a fulfillment of the stewardship/agency function) has followed the same basic routine. The tools have however changed over time, from quill and ledger to spreadsheet and specialized software. While the underlying logic of the work has however stayed the same. Artificial intelligence, together with machine learning, large-scale data analytics and cloud infrastructure are changing not just what accountants do, but how they think about what they do. This paper draws on recent systematic reviews, bibliometric studies and empirical work to make two connected arguments. The first is that AI is reshaping accounting thought, pulling the profession away from a backward-looking, compliance-first mindset toward a more predictive and strategic engagement. The second is that AI is reshaping accounting practice, automating routine work, increasing the accuracy of financial reporting, and giving fraud detection a reach that traditional sampling-based methods never had. To help organisations understand where they stand in this tectonic shift, we propose a four-tier AI maturity model for financial accounting. Attention is given to the African context, with evidence drawn from Nigeria, South Africa, Kenya and Ghana, where adoption is real but uneven, and where the constraints (infrastructure gaps, skills shortages, cost, and thin regulation) are just as instructive as the successes. The paper closes by arguing that the profession's task is not simply to adopt new tools, but to hold on to its founding commitments of trust, integrity and professional judgement while doing so.

Key words: *Artificial Intelligence, chief value officer, digital transformation, financial accounting, reengineering*

INTRODUCTION

Accounting is one of the oldest disciplined practices in commercial life. Double-entry bookkeeping, which Luca Pacioli set down in 1494, has underpinned financial record-keeping for more than five centuries (Smith, 2008). Through all that time, the core activities of the profession (recording transactions, summarising them, and preparing financial statements to show the charge and discharge aspects of the business (stewardship), has changed remarkably little in substance. While the instruments used shifted, from scrolls to ledgers and then to spreadsheets, the logic did not change much, except for accounting treatments and standards (see Whittington, 2008), that arose out of industrialization (scale) and the attendant separation of ownership and management. That long period of arduous, tool-level change now appears to be ending. The Fourth Industrial Revolution has engendered a wave of disruption built on the convergence of digital, physical and biological technologies. Artificial intelligence (AI) sits at the centre of this wave, reshaping how organisations operate, how value is created, and how financial information is produced, interpreted and communicated.

Financial accounting has not escaped this paradigm shift. On the contrary, it has been unusually exposed, because so much of accounting work is routine, rules and standards based, and data-heavy which is the kind of work AI is suited for automating and augmenting. That exposure cuts two ways. On one side is the risk of job displacement which puts real pressure on accountants to reskill quickly and on the other side, a genuine opportunity to be freed from repetitive processing and to focus more time on strategic advisory work, predictive analysis, and the kind of judgement calls that AI simply cannot make on its own. These include the contemporary accounting issues of our time such as approaches to measurement, fair value accounting, corporate governance, environmental accounting and sustainability, earnings management and the financial indicators of corporate collapse (Rankin, Stanton, McGowan, Ferlauto, & Tilling, 2012). Indeed, the accountant is now evolving to become a Chief Value Officer as opposed to the traditional 'bean counter'.

In the 1990s, Hammer and Champy (1993) popularised the idea of reengineering as rethinking business processes from first principles rather than tweaking them at the edges. Applied to accounting, that means asking not just which new tools to adopt, but what the profession is actually for, and what accountants should really be doing with their time. This paper argued that the change we are seeing right now runs along two connected tracks. The first track is about mindset. It is about the framework that accountants bring to their work. The profession is moving away from the old orientation—always looking backwards, stuck on historical cost, and putting compliance first. It is shifting towards something more forward-looking, more predictive, and more attentive to things beyond just financial capital (Rankin et. al., 2012). That is a big shift. The second track is about practice. It is about the tools, workflows and operating models that accountants use on a day-to-day basis. Think AI, machine learning, and data analytics. These are not just add-ons. They are changing how the work actually gets done. Now here is the thing: AI is the engine driving both tracks. It is a general-purpose technology. That means it does not just change what accountants do. It changes how they do it and how they understand their reshaped role in the whole process.

Research Objectives, Scope and Methodology

This paper is designed to do six things: (1) to pull together the current state of knowledge on AI in financial accounting. This draws on systematic reviews, bibliometric work and empirical studies. (2) To look at how AI is reshaping accounting thought—the shift from the historical to the predictive, from compliance to strategy, and from a purely financial view to a multi-capital one. (3) Examine how AI is reshaping accounting practice in practical terms. That means automation, better reporting accuracy, improved accounting information systems, and stronger fraud detection. (4) It sets out the main risks of adopting AI which includes ethical concerns, data quality problems, algorithmic opacity and regulatory gaps. (5) It looks specifically at the African experience, with evidence from Nigeria, South Africa, Kenya and Ghana. And (6), it proposes a maturity framework that organisations and researchers can use to assess where they currently stand on this journey

The paper's scope is deliberately limited to financial accounting which in this context is taken to include stewardship accounting, assurance, and accounting information systems. This is a conceptual paper based on a contemporaneous literature review. Sources of the literature in this paper included Scopus, Web of Science and Google Scholar using search terms that included artificial intelligence, financial accounting, financial reporting, machine learning, accounting information systems, fraud detection, and Africa. Priority was given to systematic reviews and bibliometric studies that map the field broadly, empirical studies with clearly stated methodologies, and work that speaks to the African context. Except for an introductory context, most of the literature cited was published between 2023 and 2026, reflecting just how topical and dynamic this research area is becoming.

LITERATURE REVIEW

The Evolution of AI in Financial Accounting: A Literature Overview

Academic interest in bringing together AI and accounting has grown quickly. This tracks with how fast the technology is moving and a growing recognition within the profession that this is not just a passing fad. A 2025 systematic review and bibliometric analysis of 256 articles (Sanz Martin, Parra Dominguez, Corchado, Zafra-Gomez, Castillo-Ramos and Zafra-Gomez, 2025) found that AI, blockchain and big data are doing most of the heavy lifting when it comes to enhancing accounting functions. The same study flagged a real need for closer collaboration between technologists and accountants. It also raised genuine concerns about transparency, ethics and security—concerns that point directly towards a need for regulation that can keep pace with the technology. Stoykova's (2024) bibliometric analysis, which used

Scopus data and the VOSviewer mapping tool, also confirmed a sharp rise in research output on AI and accounting from 2019 onward. There were 72 publications in 2023 alone, and 66 more by mid-2024. The United States dominates the landscape. Now, here is where things get interesting. That concentration is worth paying attention to because it implies that the evidence base is thinnest exactly where the questions about infrastructure, cost and skills gaps are most pressing—in Africa and other developing regions (Stoykova, 2024).

Ahmed's (2026) bibliometric study of 98 Web of Science articles which focused specifically on AI's effect on accounting information and earnings management, found that AI can reduce information asymmetry and increase transparency. But it also found that AI opens new avenues for more sophisticated earnings management. This is a useful reminder that these tools can cut in more than one direction. Abdo-Salloum and Chehade's (2026) systematic review reached a similar conclusion from a different angle: AI improves efficiency, strengthens fraud detection and lifts reporting credibility, but it is also shifting the auditor's role from retrospective inspection toward continuous, real-time monitoring, arguably the single most consequential change identified in this literature for how audit and assurance work will actually be structured going forward.

Key Application Areas of AI in Financial Accounting

Four areas stand out in the literature as to where AI is having the clearest impact on financial accounting practice. The most visible use of AI remains automating rules-based, repetitive work including data entry, transaction coding, reconciliation and summarising, and drafting standard reports. Abdo-Salloum and Chehade (2026, *ibid.*) note that this automation now extends well past simple data entry, into drafting financial statements and flagging anomalies that may point to error or fraud. On reporting accuracy and transparency, Johri (2025) surveyed 566 accountants and finance officers across India and found that AI meaningfully improves the quality of accounting information systems, with both AI and internal controls mediating the link between system quality and reporting accuracy. Separately, Alslaibi, Alshdaifat, Bani Hani, Abu Farha and Alhasnawi (2025), studied small and medium enterprises in emerging economies, found that AI tools (expert systems, automated learning and neural networks) do improve voluntary disclosure and transparency, but only where the underlying accounting information systems are themselves reliable. Put plainly: AI amplifies what is already there; it does not fix broken systems on its own. Another way to phrase this is that, regardless of having AI tools and accounting systems, an organisation with a dysfunctional culture will not benefit positively from their use. Firms must have the right behavioural norms to drive performance that increases shareholder value.

With regard to predictive analytics, Kureljusic and Karger's (2024) systematic review of 47 studies identified earnings prediction, cash-flow prediction and bankruptcy prediction as the three main areas where AI-based forecasting is being applied in financial accounting. The shift from recording what happened to forecasting what is likely to happen is arguably the clearest expression of what reengineering accounting thought means in practice. On fraud detection and audit/assurance, machine learning is being used to catch patterns that traditional, sample-based audit approaches would miss. Chen, Chen, Liu and Shi (2026) propose a hybrid model capable of detecting five distinct categories of financial statement fraud simultaneously. These are inflated profits, inflated assets, false statements, delayed disclosure, and omission of material information, rather than treating fraud as a single yes-or-no outcome. A Nigerian study, (Chinumezi, Ichenda, Innocent, & Florence, 2025), using natural language processing and interpretable models, drawing on 400 professionals across banks and financial institutions in Port Harcourt, found that AI-assisted fraud detection improved auditor confidence and risk assessment, specifically because the outputs were explainable and not opaque.

Reengineering Accounting Thought: The Cognitive and Philosophical Shift

Financial accounting has always tended to look backward by design because accountants were expected to render a periodic report of the firm’s performance to shareholders who were not involved in the day to day running of the business. In line with IFRS requirements, a balance sheet reports a position at a point already passed. An income statement summarises operations that have already concluded and a cash flow statement records movements that have already happened. AI does not eliminate this backward-looking function, but it adds a forward-looking one alongside it including using historical data to identify patterns that inform what is likely to happen next. Kureljusic and Karger (2024) group this forward-looking work into earnings, cash flow and bankruptcy prediction, each of which pushes accounting beyond its traditional remit toward something closer to strategic forecasting. The practical effect is a change in the accountant's core question: from "what happened?" to "what is likely to happen, and what should we do about it?"

The accountant's traditional role has also centred on standards-based compliance — making sure statements meet applicable standards and regulatory requirements. That does not disappear, but as routine compliance work is automated, accountants have more time for interpretation, strategic input and decision support. Abdo-Salloum and Chehade (2026) describe this shift in audit terms: from retrospective inspection to real-time monitoring. That changes not just the timing of the audit, but the auditor's entire relationship with the organisation being audited. Accounting thought has historically been organised almost entirely around financial capital which implies assets, liabilities, financial performance (profitability), and cash movements. AI, alongside the broader sustainability reporting agenda, is helping widen that lens to include human, social, natural and intellectual capital. It does so largely by making it feasible to process the volume of ESG-related data needed to connect these factors to financial performance in a systematic way. Emerging frameworks such as integrated reporting and the ISSB sustainability standards already reflect this broader understanding of value creation.

Materiality has traditionally been treated as a relatively fixed threshold. For long we argued that information matters if its inclusion/omission could plausibly affect a user's (shareholders, lenders, suppliers, customers and regulators) decisions regarding the firm. What AI makes possible is continuous monitoring of the environment for shifts that change what counts as material. Carbon emissions are an example: financially immaterial for most companies a decade ago, now highly material because of carbon pricing, regulatory pressure and investor expectations. AI-supported monitoring allows accountants to track that kind of shift as it happens, rather than discovering it at the next reporting cycle.

Reengineering Accounting Practice: The Operational and Technological Transformation

Abdo-Salloum and Chehade (2026) found AI improved operational efficiency and reporting credibility largely through automating routine work across the accounting function, from transaction processing through to reporting and audit. Today’s accountant does not have to distinguish which side of the ‘t-account a transaction should be posted! AI driven software easily addresses the dual nature (debit and credit) of transactions that are posted into the accounting information system. But the more interesting change is not simply the substitution of machine effort for human effort. Tasks once performed in sequence by different people can now run concurrently. Processes that once needed a manual sign-off at each stage can run end to end without it. That is a redesign of the workflow itself, not just a faster version of the old one.

Johri's (2025) finding that AI significantly improves the quality of accounting information systems when mediated by internal control systems (and culture), suggests that AI is best understood as a component of a well-functioning accounting information system, not an add on. The practical consequence of this observation is that organisations that invest in AI-enhanced accounting information systems gain more reliable financial information and, over time, a real edge in stakeholder confidence over those that do not. In addition, in line with the qualitative characteristics of financial accounting, (relevance, faithful representation, comparability, verifiability, understandability and timeliness) perceptions of reliability are increased (Mbobo and Ekpo, 2016).

Traditional audit/assurance relies on testing a sample and drawing conclusions about the whole population. AI makes continuous auditing possible by providing the capacity to examine all transactions, in real time. Abdo-Salloum and Chehade (2026) trace several downstream effects of this shift and note that audit risk falls significantly because anomalies across the full population are visible rather than just those caught in a sample. Audit quality rises because auditors can direct attention to the highest-risk areas as assurance becomes continuous as opposed to being periodic. In addition, new and novel audit capabilities become possible, for example sentiment analysis of management communications and predictive assessment of going-concern risk.

Chen, Chen, Liu and Shi's (2026) multi-label hybrid model moves fraud detection past the single-category, red-flag approach that has dominated the field thus far to allowing several distinct types of fraudulent behaviour to be identified in the same case. In Nigeria, the Port Harcourt study cited earlier (Chinumezi *et al*., 2025) found that interpretable AI models not only improved detection accuracy but also the auditors trust in the results. This is very important because a fraud-detection tool that nobody trusts enough to act on is of limited practical value, irrespective of how accurate it may be.

Challenges, Risks, and Critical Considerations

Many AI systems, especially deep learning models, are hard to interpret. This creates a real problem for auditors, regulators and other stakeholders who need to understand how an AI-generated figure was arrived at. Sanz Martin et al. (2025) point to this as a direct barrier to trust. The reason? Opacity. If you cannot verify how a result was derived, it is difficult to rely on it with confidence. And if it turns out to be wrong, it is even harder to assign responsibility. That is a serious concern. If you cannot verify how a result was derived, it is difficult to rely on it with confidence. And if it turns out to be wrong, it is even harder to assign responsibility. That is a serious concern.

Now, here is where it gets interesting. The Port Harcourt fraud-detection study (Ibid.) found that interpretability tools like SHAP (SHapely Additive exPlanations) and LIME(Local Interpretable Model-Agnostic Explanations) did more to build auditor confidence than raw accuracy scores. That tells us something important: explainability is what earns an AI system a place in the workflow. AI is only as good as the data behind it. Alslaibi *et al.* (2025) found that AI's contribution to transparency depends on the reliability of the underlying accounting information system. Where that foundation is weak, AI cannot compensate for its lack of reliability, and such a system only serves to amplify the underlying flaws. This is a particular concern across much of Africa, where manual processes and limited digitisation remain common. In many cases, the real constraint on AI adoption is not the technology itself; it is the absence of clean, reliable digital data on which the technology depends. In Uganda, the government embarked on a project to mainstream data analytics and AI and create national AI strategy. However, it was obvious from the start, that the lack of centralized databases that are also compatible, was a bigger hindrance to the project than the promulgation of an AI strategy itself. The lesson is stark: you cannot use AI effectively at both the micro and macro levels, if your data (information systems) is not centralized or seamless.

AI adoption in accounting raises a familiar cluster of ethical questions such as job displacement. As routine roles are automated, algorithmic bias which is inherited from the ethnocentric approach to training large language models, privacy concerns related to the security of the large volumes of data ceded to AI systems and the more complex role for professional judgement as AI takes on more of the operational load inevitably arise. Abdo-Salloum and Chehade (2026) have listed high costs, ethical concerns, uneven regional readiness and a thin empirical base among the practical barriers to adoption. Sanz Martin *et al.* (2025) reach a similar view on the ethical and security side. Standards and regulation development have not kept pace with the technology advancement. Existing accounting rules were written for a world before AI, and do not yet answer basic fourth and fifth industrial generation dilemmas. How should AI-generated financial information be audited? How should the reliability of the AI system itself be assessed? Where does responsibility sit when AI is involved in producing a figure that turns out to be wrong? Sanz Martin et al. (2025) call for regulation evolution that can adapt at something closer to the pace of the technology. This is difficult for standard-setters who have limited proprietary information about these AI systems and need to avoid stifling useful innovation.

None of these systems can work without people who can use them properly. Accountants increasingly need data analytics skills, AI literacy and technical fluency to work alongside specialists to exercise genuine oversight of AI systems. This requires a different skill set from that accorded by traditional accounting training. Sanz Martin et al. (2025) point specifically to the need for closer collaboration between technologists and accountants. The technology gap associated with accounting and implementation of AI systems is more acute in parts of Africa where education and training systems have been slower to adapt. Without deliberate investment, the benefits of AI adoption risk concentrating in a small number of organisations rather than spreading through the profession more broadly. Rwanda stands out as a country where a deliberate effort has been made to develop a knowledge-based economy as a basis for transformation. The impact of the country's STI (Science, Technology and Innovation) program has led to greater use of AI in eGovernment and firms (Nkusi, 2025). The eGovernment systems in Rwanda, which are AI driven, have reduced human contact, thereby further reducing rent seeking tendencies of public officers while increasing the country's rating in the World Bank's "Doing Business" Reports.

The African Context: Opportunities and Challenges

AI adoption in accounting by African countries is in the early stages but inevitable. It is also not evenly spread, on account of the resource constraints faced by some countries, alongside poor national adaptation policies. Olaoye (2025) surveyed CFOs and accountants across 30 multinational companies in Nigeria, South Africa and Kenya with a documented history of AI adoption, and found meaningful gains which included reduced human error, more streamlined processes, and faster reporting. South Africa led the way, followed by Kenya and then Nigeria. Gwar and Agboluga's (2026) review of AI's role in financial accountability and governance in Nigeria reaches a broadly consistent conclusion that AI can strengthen oversight and fiscal discipline where appropriate regulatory and ethical frameworks are in place. But Nigeria's regulatory gaps, limited technical capacity and the absence of a comprehensive AI legal framework remain real constraints on how much progress can be achieved in the medium to long term.

Several studies focused on Nigeria add texture to the broader picture. Otuedon *et al.*'s (2025) study of accounting firm performance in the Nigerian hospitality sector found that Meta AI tools lowered costs, improved data-analytic capabilities and strengthened client service. This is a useful and specific data point precisely because it examines one sector rather than averaging across many. Furthermore, Alslaibi *et al.'s* (2025) findings on AI-based disclosure and transparency, while framed around emerging-economy SMEs generally rather than Nigeria specifically, are consistent with what the Nigeria-focused literature reports. Researchers agree that while AI is helpful, it is only as good as the underlying systems.

Agbenorxevi *et al.* (2026) examined AI-supported accounting practices among 367 female artisan entrepreneurs Ghana. They found that value-risk perception moderates the relationship between digital financial literacy and financial reporting quality. As digital financial literacy improves, financial reporting quality also improves because of the digitals applications' ability to keep records of their transactions. What makes this study stand out alongside the multinational-firm evidence, is its focus on the informal and micro-enterprise end of the economy, and its explicit attention to gender, a segment almost entirely absent from the larger-firm studies that dominate this literature. This is, arguably also the sector where digital financial literacy matters most because of its connect to both formality and informality.

Taken together, these studies point to a somewhat consistent pattern. First, adoption is uneven across the continent when tracking differences in infrastructure, digital skills and economic development. South Africa is generally ahead of Kenya and Nigeria. Second, where AI has been adopted, the reported benefits are real with fewer errors, faster processes, and better client service. But adoption is heavily skewed toward larger, multinational organisations, with SMEs and informal enterprises lagging well behind. Third, the studies converge on the same underlying point from different directions: how much AI delivers depends on contextual factors such as digital financial literacy, risk perception, system reliability rather than on the sophistication of the AI itself. What seems to have not been examined extensively as a control variable, is the impact of culture on these factors.

African organisations may be able to leapfrog legacy systems entirely, rather than upgrading them incrementally. AI can make accounting for SMEs and informal enterprises more efficient and more accurate while supporting financial inclusion. Better fraud detection can help tackle illicit financial flows, which are a significant problem across much of the continent. Improved reporting quality and transparency can help build investor confidence. This is something African markets sorely need. These opportunities sit alongside real constraints such as infrastructure, reliable power, connectivity, and cloud access which remain patchy in many countries. Digital skills shortages limit how far organisations can go even where the technology itself is available. Costs also put meaningful AI adoption out of reach for many organisations. And the absence of settled regulatory frameworks creates uncertainty that itself discourages investment. Addressing these constraints is not a secondary concern. Rather it is the prerequisite for the opportunities to materialise.

A Framework for AI Maturity in Financial Accounting

The literature reviewed here emphasizes that AI adoption in financial accounting sits at very different stages depending on the organisation and the country. What is missing is a simple, practical way for organisations to locate themselves on that journey and think clearly about what comes next. The four-tier model below is being proposed for that purpose. It has been developed based on the literature reviewed and informed by maturity models used in other fields.

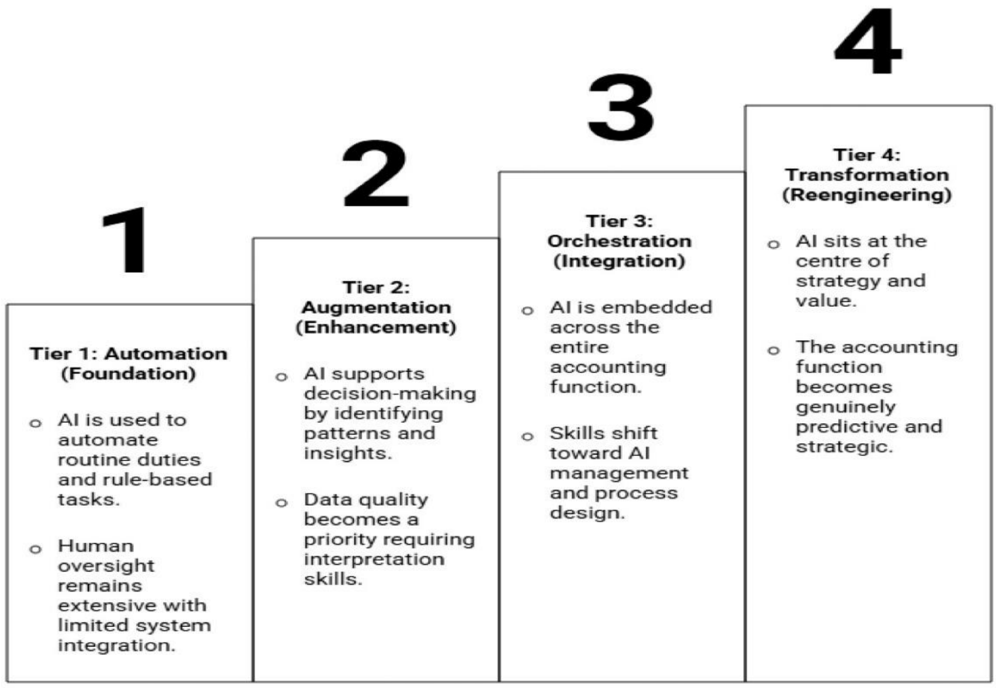
Tier 1: Automation (Foundation). At this level, AI is used or being used to automate routine duties, rule-based tasks: transaction processing, data entry, reconciliation, and standard report generation. Human oversight remains extensive while integration with existing systems is limited, and the skills required are largely basic digital literacy. Abdo-Salloum and Chehade's (2026) examples of automated transaction coding and draft-statement preparation sit at this tier.

Tier2: Augmentation (Enhancement). At this level, AI supports decision-making rather than executing repetitive tasks. It involves identifying patterns and discovering insights. Human control is still evident regarding the final call. Data quality becomes a recognised priority, and the skills required shift toward data interpretation and basic AI literacy. Johri's (2025) findings on AI-enhanced accounting information systems, and the AI-supported fraud detection work discussed earlier, both sit here.

Tier 3: Orchestration (Integration). AI is now embedded across the accounting function rather than confined to specific tasks, and human and machine intelligence work together as a matter of course. Integration across systems is comprehensive, and the skills required move toward AI management and process design. Continuous auditing and forecasting are embedded directly into decision-making as described by Abdo-Salloum and Chehade (2026) and Kureljusic and Karger (2024) at this level.

Tier 4: Transformation (Reengineering). At the highest tier, AI sits at the centre of strategy and value creation. At this stage, the accounting function has become genuinely predictive and strategic, and multi-capital reporting is fully integrated. There are very few organisations in the world, that currently operate at this level. It represents the logical endpoint of the reengineering argument this paper has been making throughout. The conceptual framework below illustrates the proposed maturity model for AI adoption in financial accounting.

Figure 1: A Maturity Model for AI Adoption in Financial Accounting



Source: Literature Review

Organisations can use this framework to locate their current position and map a path forward. Researchers can use it to classify organisations and study what enables movement from one tier to the next. The model has relevance in the African context, where most organisations are likely sitting at Tier 1 or Tier 2, with only a small number approaching Tier 3. The framework's real value, perhaps, is in making explicit that AI adoption is a multi-year journey rather than a single decision. Each step up requires investment across the three aspects of technology, skills, and organisational change. Organisations that succeed under this framework must have a well-defined ‘theory of change’. Understanding that is itself a useful starting point.

CONCLUSION

This paper set out to examine how artificial intelligence is reshaping both the thought and the practice of financial accounting. Several conclusions follow from the literature reviewed. The pressure to adapt AI in financial accounting is real and immediate, driven by the convergence of AI, machine learning, big data and cloud computing. At the contemplative level, AI is enabling a shift from backward-looking historical reporting toward forward-looking prediction, from compliance-first work toward strategic advisory, and from a purely financial view of capital toward a multi-capital one. At the pragmatic level, AI is automating routine work, improving the quality of accounting information systems, changing what audit and assurance look like, and giving fraud detection considerably more reach.

None of this comes without cost. Algorithmic opacity, data quality problems, ethical concerns, and regulatory gaps are all real and unresolved challenges that will need sustained attention from organisations, professional bodies and regulators alike. In Africa specifically, adoption is in its early stages. South Africa is generally ahead of Kenya and Nigeria. At the firm level, it is possible to leapfrog and leverage the real opportunities of AI adoption. However, this requires investment to address the constraints caused by infrastructure deficits, skills gaps, cost barriers and regulatory compliance. The four-tier maturity model proposed here is intended as a practical blueprint for organisations to think through where they currently sit and what the next step requires.

For accounting professionals, this shift requires investment in data analytics, AI literacy and technology management, alongside the traditional accounting skill sets. The accountant's role is also changing from one of being a transaction processor towards becoming the go to strategic advisor of the executive committee and the Board. Experience shows that the skills that the new role demands are not the ones most accountants were trained for. In accounting firms, AI capability is no longer optional for any firm that wants to remain competitive, they are a must. That implies investment in technology, retraining and retooling, and a paradigm shift regarding the firm’s value proposition.

For recognised supervisory bodies (RSB’s) and the International Federation of Accountants (IFAC) the role in continuing standards and professional development, curriculum reform and guidance for responsible AI adoption is arguably more urgent than ever before. Frameworks that address algorithmic transparency, auditability and where professional responsibility sits when AI is involved in information production are needed. Current standards simply do not answer these questions. For educators, accounting curricula need to evolve to include data analytics and AI literacy alongside traditional accounting knowledge to prepare students for a profession that will look materially different from what it is today.

There are also several gaps in the extant literature. There is a clear need for more empirical work on AI adoption in African accounting using both quantitative and qualitative approaches to understand what enables or constrains adoption. Comparative studies across countries, sectors and organisation types would help identify which contextual factors matter most. The intersection of AI with multi-capital accounting (ESG reporting, integrated reporting, and sustainability accounting) remains underexplored as well. AI ethics and governance in accounting specifically also need more attention. The four-tier maturity model proposed here is a starting point that may be adopted and refined.

The main thesis of this paper is that: AI is changing both what accountants do, how they do it, and how they think about what they do. Neither change means much without the other. An accounting function with a reengineered mindset but the same old tools has good intentions and no capability to act on them. An accounting function with advanced tools but an unreformed sense of purpose has capability without direction.

The more useful future sits at the intersection of human judgement and machine intelligence. That is a future in which accountants are freed from routine work to focus on what genuinely requires their judgement, where financial information is more accurate and timelier, and where the profession contributes more directly to organisational and societal outcomes than it currently does. That journey has already begun in earnest. The question is not whether the profession will be reengineered, but how quickly and how well we will adapt. That depends on the choices being made now by academics, advisory firms, professional bodies, and standard setters.

REFERENCES

Abdo-Salloum, A. M., & Chehade, S. (2026). The role of artificial intelligence in transforming accounting and auditing practices: A systematic review. SAGE Open.

Agbenorxevi, C. D., Hevi, S. S., Malcalm, E., & Ketemepi, G. E. (2026). Intermediate-level AI-supported accounting practices and financial reporting quality among female artisan entrepreneurs in Ghana. *Journal of Entrepreneurship and Public Policy*, 1-19.

Alslaibi, N. A., Alshdaifat, S. M., Bani Hani, L. Y., Abu Farha, E. K. K., & Alhasnawi, M. Y. (2025). Artificial intelligence and financial statement transparency: The moderating role of accounting information systems' reliability. EDPACS, 71(5), 17-29.

Ben Ahmed, D. (2026). The impact of artificial intelligence on accounting information and earnings management: Bibliometric analysis. *Journal of Risk and Financial Management*, 19(1), 90.

Chen, Z., Chen, H., Liu, Y., & Shi, Y. (2026). Multi-label financial statement fraud detection based on long short-term memory and multilayer perceptron hybrid model. *Engineering Applications of Artificial Intelligence*, 170, 114188.

Chinumezi, T. J., Ichenda, O. V., Innocent, E., & Florence, O. (2025). Effectiveness of artificial intelligence in detecting financial statement fraud. *American Journal of Economics and Business Management*, 8(8), 4127–4141.

Gwar, S., & Agboluga, A. B. I. (2026). Artificial intelligence for financial accountability, corporate governance, and economic sustainability: An overview. *Gusau Journal of Accounting and Finance.*

Johri, A. (2025). Impact of artificial intelligence on the performance and quality of accounting information systems and accuracy of financial data reporting. *Accounting & Finance.*

Kureljusic, M., & Karger, E. (2024). Forecasting in financial accounting with artificial intelligence: A systematic literature review and future research agenda. *Journal of Applied Accounting Research*, 25(1), 81-104.

Mbobo, M. E., & Ekpo, N. B. (2016). Operationalising the qualitative characteristics of financial reporting. *International Journal of Finance and Accounting*, 5(4), 184-192.

Nkusi, A. C. (2025). Industrial, Science and Technology Policy in Rwanda. *Annals of Science and Technology Policy*, 9(1), 111-151.

Olaoye, A. A. (2025). Artificial intelligence and enhancing accounting practices in selected African countries. *Jurnal Akuntansi*, 17(1), 36-50.

Otuedon, M. A., Okonkwo, G. E., Togbolo, S. E. U., Amughoro, A. O., Ubogu, F. E., Efanimjor, P., Atube, E.N. and Etu, T.A., (2025). Impact of meta-AI on accounting firm performance: implications for the hospitality business in Nigeria. Management:(Montevideo), 3, 3.

Rankin, M., Stanton, P., McGowan, S., Ferlauto, K., & Tilling, M. (2012). *Contemporary Issues in Accounting*. Wiley & Sons.

Sanz Martin, L., Parra Dominguez, J., Corchado, J. M., Zafra-Gomez, E., Castillo-Ramos, V., & Zafra-Gomez, J. L. (2025). Recent evolution and growth of AI and advanced technologies in accounting and finance: Systematic review and bibliometric analysis.

Slyozko, T., & Zahorodnya, N. (2016). The fourth industrial revolution: The present and future of accounting and the accounting profession. Polgari Szemle.

Smith, F. (2008). The influence of Amatino Manucci and Luca Pacioli. BShM Bulletin, 23(3), 143-156.

Stoykova, A. (2024). AI in accounting: Insights from a bibliometric analysis. CECCAR Business Review, 5(8), 56-71.

Whittington, G. (2008). Harmonisation or discord? The critical role of the IASB conceptual framework review. *Journal of Accounting and Public Policy*, 27(6), 495-502.