ARTIFICIAL INTELLIGENCE IN ACCOUNTING

Artificial Intelligence as a Catalyst for Change in Accounting and Finance: Exploring Applications, Opportunities and Challenges

Rekha Susan Leo

SJES College of Management Studies, Medahalli, Bangalore, India

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Abstract

Artificial Intelligence (AI) is changing accounting and finance by shifting technology from a back-office automation role toward a broader capability for analysis, prediction, monitoring and decision support. This paper examines how Machine Learning, Natural Language Processing, Robotic Process Automation, Optical Character Recognition, Generative AI and Explainable AI are being applied across accounting and financial activities. An integrative literature review is used to synthesise recent peer-reviewed research and authoritative professional and regulatory publications, with particular attention to developments through 2026 and the Indian context. The review indicates that AI creates value through faster transaction handling, continuous anomaly detection, improved forecasting, document analysis, risk assessment and expanded access to financial insight. At the same time, the value of AI is conditional rather than automatic. Weak data, limited explainability, privacy concerns, cybersecurity threats, biased models, inaccurate generative outputs and excessive reliance on automated recommendations can undermine the quality of financial decisions. The paper identifies a further shift in professional work: accountants and finance professionals are likely to spend less time on repetitive processing and more time on exception analysis, interpretation, governance, advisory work and strategic decision support. Based on the synthesis, the paper proposes a Human-Centred AI Transformation Model linking AI capabilities to functional applications, process outcomes, professional transformation and organisational value, with data quality, governance, human oversight and AI literacy acting as safeguards. The paper contributes an integrated view of AI across accounting and finance and argues that sustainable adoption depends on combining technological capability with professional judgement, ethical responsibility and institutional controls. The study recommends investment in data foundations, formal AI governance, continuous professional development, explainability and human review for material accounting and financial decisions.

Keywords: Artificial Intelligence; accounting; finance; Generative AI; auditing; AI Governance

1 Introduction

Accounting and finance are information-intensive functions. Their outputs influence investment decisions, internal control, taxation, lending, performance measurement and public confidence. For decades, digital systems have reduced the effort required to record, store and retrieve financial information. The current stage of technological change is different because AI can do more than execute fixed instructions: it can identify patterns, classify information, generate predictions, interpret language and support human decisions. This capability is bringing technology deeper into the judgement and analytical layers of accounting and finance.

The academic literature now shows a broadening research agenda. Murphy et al. (2024) mapped accounting and AI research and identified a diverse set of themes, while Dong et al. (2024) showed that research on ChatGPT and large language models in accounting and finance has expanded beyond simple experimentation into questions about professional work, research methods and organisational implications. More recent reviews further demonstrate that the field is becoming mature enough to require integrated frameworks rather than isolated lists of applications. Sanz Martin et al. (2026), for example, synthesised 256 articles and highlighted collaboration, transparency, ethics, security and skills as central issues. Abbas (2026) reviewed 91 studies on management accounting and concluded that emerging technologies are changing accounting information, organisational relationships, professional boundaries and skill requirements.

The finance side of the literature presents a similar pattern. Singh et al. (2025) reviewed 157 studies of AI in banking and finance and found recurring attention to customer service, financial inclusion, regulation and explainability. The implication is that AI is no longer confined to specialised quantitative models. It is becoming embedded in customer-facing, operational and governance activities.

The challenge, therefore, is not simply deciding whether AI is useful. The more important questions are where AI adds reliable value, what risks accompany that value, which professional activities should remain under human control, and what capabilities organisations must build to use AI responsibly. These questions are especially relevant in India, where ICAI is expanding AI capability for the accounting profession and where RBI and SEBI are developing responsible-use approaches for financial services and securities markets (ICAI, 2026; RBI, 2025; SEBI, 2025).

This paper addresses these questions through an integrative review and develops a conceptual model that places professional judgement and governance alongside technology. Its central argument is that AI should be treated as an organisational capability rather than as a software purchase. Technology can accelerate a process, but organisational value depends on the quality of data, the suitability of the task, the competence of users and the strength of controls.

2 Problem statement and research gap

Existing literature is rich but fragmented. One stream examines AI in auditing; another studies management accounting; a third investigates banking, credit, investment or customer service. Generative AI adds another stream focused on natural-language interaction, document interpretation and knowledge work. These streams often use different outcome measures and different assumptions about what constitutes successful adoption. As a result, it is difficult to see how an accounting or finance organisation should move from a specific AI application to a coherent transformation strategy.

A second gap concerns the relationship between efficiency and professional value. Much discussion still treats AI adoption as synonymous with automation and cost reduction. Recent evidence suggests a broader transition: finance functions are expected to become more strategic and to take greater responsibility for data stewardship, AI governance and trusted insight (ACCA & CA ANZ, 2026). The unresolved question is how this transition can be achieved without weakening professional scepticism or accountability.

A third gap concerns the Indian setting. India has an active digital financial ecosystem and a large accounting profession, while professional and regulatory institutions are visibly moving toward

responsible AI adoption. Yet accounting research often discusses AI in a generic international setting. Bringing professional transformation and governance into an India-relevant framework can therefore provide a useful bridge between academic discussion and practice.

3 Objectives of the study

1. To identify the major applications of AI across accounting and finance functions.
2. To synthesise the principal opportunities created by AI-enabled processes.
3. To analyse the technological, ethical, professional and regulatory challenges associated with AI adoption.
4. To examine how AI changes the nature of accounting and finance work and the skills required of professionals.
5. To develop a human-centred conceptual framework for AI-enabled accounting and finance.
6. To propose practical measures for responsible and value-oriented AI adoption.

4 Research questions

1. What accounting and finance activities are most affected by AI technologies?
2. What forms of organisational value can AI create in these activities?
3. What conditions limit or strengthen the value of AI adoption?
4. How is AI changing professional roles and competence requirements?
5. What governance mechanisms are necessary for trustworthy AI-enabled accounting and finance?

5 Methodology

This study uses an integrative literature review. The approach was selected because the topic spans multiple technologies and professional settings and because the objective is to connect findings across accounting, auditing, finance and governance rather than estimate a single pooled effect. The review emphasises peer-reviewed research published from 2020 to 2026, while retaining earlier foundational work where it remains relevant to an argument. Authoritative publications from ACCA, ICAI, RBI, SEBI and the Financial Reporting Council were included where they provide evidence about current professional or regulatory practice.

The literature was organised using five analytic categories: (i) AI capability, (ii) functional application, (iii) organisational opportunity, (iv) risk and governance, and (v) professional transformation. Studies were selected for direct relevance to accounting, auditing, financial management, banking, investment or professional practice. Sources that were primarily technical and unrelated to accounting or finance were not used as core evidence. The resulting synthesis is interpretive rather than a formal meta-analysis; no effect sizes are estimated and no claims of statistical generalisation are made.

The review process is also intentionally transparent about its limits. The paper does not claim to be an exhaustive database census. Instead, it uses recent high-relevance studies and official institutional evidence to build and test a coherent conceptual argument. This is appropriate for a conference paper whose contribution is the integration of application, opportunity, risk and professional transformation.

6 Review of selected literature

The selected studies show an evolution from asking whether AI can automate accounting tasks to asking how AI should be integrated into professional systems. Table 1 summarises representative contributions that inform the present framework.

Table 1. Representative literature on AI in accounting and finance.

Study	Context	Focus	Relevance to present paper
Lehner et al. (2022)	Accounting and auditing	Ethics of AI decision-making	Objectivity, privacy, transparency, accountability and trust are central ethical concerns.
Abdullah & Almaqtari (2024)	Accounting and auditing	AI, Industry 4.0 and practice	AI-related capabilities were associated with improved accounting and auditing practices in an emerging-economy setting.
Murphy et al. (2024)	Accounting	Topic modelling of literature	AI research in accounting is broad and increasingly focused on value creation and new research directions.
Dong et al. (2024)	Accounting and finance	ChatGPT and LLMs	LLMs are being studied for applications, research support and professional implications.
Murikah et al. (2024)	Auditing	Bias and ethics	Bias can arise from data, model design and human decision processes; governance and monitoring are needed.
Vitali & Giuliani (2024)	Auditing firms	Organisational change	Digital technologies may change audit firm structures, skills and competitive dynamics.
Singh et al. (2025)	Banking and finance	Systematic review of 157 studies	AI applications span customer service, inclusion, regulation and explainability.
Kokina et al. (2025)	Auditing	Field evidence	Simple AI is more widely used than complex AI; explainability, reliability, privacy and overreliance remain barriers.
Stratopoulos & Wang (2025)	Accounting research	Framework and agenda	GenAI and LLMs create new research opportunities and new methodological questions.
Abbas (2026)	Management accounting	Systematic review of 91 studies	AI changes information flows, organisational relationships, roles and skill requirements.
Sanz Martin et al. (2026)	Accounting and finance	Systematic review and bibliometrics	The field increasingly emphasises transparency, security, skills and cross-disciplinary collaboration.

Taken together, these studies point to three conclusions. First, AI is entering accounting and finance through multiple pathways rather than a single technology. Second, organisational value depends on how AI is embedded in workflows and decision rights. Third, the governance problem grows as AI moves from clerical tasks toward material judgements. This third point is particularly important for the proposed framework.

7 Applications of AI in accounting

7.1 Transaction processing and bookkeeping

AI-enabled accounting systems can classify transactions, extract information from invoices and learn from historical coding patterns. When integrated with RPA and OCR, the technology can reduce

repetitive data-entry work and route unusual items for human review. The strongest use case is not necessarily full automation; it is the redirection of human attention toward exceptions, ambiguous transactions and policy-sensitive decisions.

7.2 Accounts payable and receivable

Invoice data can be extracted and compared with purchase orders, goods-received records and prior transactions. Similar techniques can support receivables by identifying overdue patterns, prioritising follow-up and estimating expected payment behaviour. These applications illustrate a broader principle: AI is particularly useful when the process contains a large volume of repetitive records but also benefits from a controlled exception path.

7.3 Reconciliation and control monitoring

Bank reconciliation and inter-ledger matching require repeated comparison. AI can help identify likely matches and surface unmatched or unusual items. This can strengthen control efficiency, but it should not remove the control owner. The user still needs to understand why an item was matched or flagged, especially when the underlying transaction has legal, tax or reporting implications.

7.4 Financial reporting and management information

AI can support consolidation, variance analysis, narrative summaries and the detection of inconsistent values across documents. Generative AI can produce first-draft commentary, but the output should be treated as draft material. Financial reporting requires verified numbers, appropriate accounting treatment and documented judgement; language fluency does not establish factual correctness.

7.5 Auditing

Audit is a high-value area for AI because audit evidence exists in large populations of transactions and documents. Machine-learning approaches can identify unusual entries and risk patterns; NLP can help analyse contracts and narrative disclosures; OCR can extract information from documents. Gu et al. (2024) describe a co-piloted model in which foundation models assist auditors, while Kokina et al. (2025) show that practical adoption remains more advanced for relatively simple tools than for complex AI. The appropriate direction is therefore augmentation: AI expands the auditor's analytical reach while the auditor remains responsible for evaluation and conclusion.

7.6 Tax and compliance

AI can support tax research, document comparison, classification and compliance checks. Its usefulness is highest when it is connected to controlled source material and when the professional can verify the underlying authority. In tax work, a confident but incorrect answer can create financial and compliance exposure, making source validation essential.

8 Applications of AI in finance

8.1 Forecasting and planning

Financial planning increasingly combines accounting information with operational data. AI can identify nonlinear relationships, detect changes in demand and improve scenario generation. The

result can be faster forecasting and a wider range of scenarios, although model performance remains dependent on data quality and on whether historical relationships remain stable.

8.2 Fraud detection and anomaly monitoring

Fraud is often characterised by deviations from normal behaviour. AI can monitor transaction streams, identify unusual combinations of attributes and prioritise cases for investigation. In India, RBI has reported the use of an AI/ML model called MuleHunter.AI to detect potential mule bank accounts. This illustrates the practical movement of AI from research into financial-crime controls (RBI, 2025).

8.3 Credit risk

AI can assist credit assessment by analysing transaction histories, repayment patterns and other information. Machine-learning approaches can improve discrimination between risk categories, but the issue of fairness becomes important. Models need testing for unintended bias, explainability and consistency with lending requirements. Explainable machine learning has therefore become an important line of research in finance (Bussmann et al., 2021; Singh et al., 2025).

8.4 Investment analysis

AI can process market data, financial disclosures and text signals to support investment research. Its role ranges from classification and sentiment analysis to portfolio and risk analytics. Human judgement remains important because market conditions change and model outputs can be sensitive to assumptions, data windows and structural breaks.

8.5 Customer service and financial inclusion

AI-powered conversational tools can handle routine customer queries and provide personalised support. Singh et al. (2025) identify customer service and financial inclusion as major themes in the finance literature. The opportunity is significant, but automated customer decisions require safeguards for privacy, fairness and access, particularly when customers have limited digital literacy.

8.6 Regulatory technology

Financial institutions can use AI to monitor transactions, identify patterns relevant to compliance and analyse large volumes of regulatory material. The key organisational benefit is scale: systems can review more information more frequently. The challenge is ensuring that compliance teams can explain, challenge and document AI-based alerts.

9 Opportunities created by AI

The literature suggests that the value of AI in accounting and finance extends beyond simple labour substitution. Six opportunity areas are especially important.

1. **Productivity:** repetitive work can be completed faster, creating capacity for higher-value activities.
2. **Analytical depth:** large datasets can be examined for patterns that are difficult to detect manually.
3. **Timeliness:** continuous or near-real-time analysis can replace delayed periodic review for selected controls.

4. **Predictive capability:** models can support forecasts, risk estimates and scenario analysis.
5. **Professional leverage:** accountants and finance teams can focus more on interpretation, challenge and advice.
6. **New service models:** AI skills create demand for AI assurance, model governance, data stewardship and technology-enabled advisory work.

ACCA and CA ANZ's 2026 research reinforces the strategic opportunity. Based on a global survey of 1,600 finance professionals, the report argues that finance can move from retrospective reporting toward enterprise-wide insight, while noting that data quality, skills and integration remain major barriers (ACCA & CA ANZ, 2026). This is important because it reframes AI adoption as a finance-function design issue rather than merely a software implementation issue.

10 Challenges and risks

10.1 Data quality and model reliability

AI systems learn from data, so errors or missing information can become systematic rather than occasional. A flawed rule in a manual process might affect a small set of transactions; a poorly designed automated rule can affect thousands. Data lineage, validation and monitoring must therefore be treated as control activities rather than technical housekeeping.

10.2 Privacy and confidentiality

Accounting records can contain payroll, customer, supplier and tax information. Feeding such information into uncontrolled external AI services can create confidentiality risk. Organisations need policies specifying which information may be used, where it may be processed and who can access the resulting outputs.

10.3 Cybersecurity

AI systems create additional points of attack and can become part of fraud or manipulation strategies. Security controls need to cover model access, data pipelines, prompts, connected applications and output handling, not only the underlying accounting database.

10.4 Bias and fairness

Bias can enter through data selection, labels, model design, proxy variables or human interpretation. Murikah et al. (2024) identify multiple technical and human sources of bias in auditing and emphasise monitoring, testing and human oversight. In finance, the issue is especially material where AI supports credit or customer decisions.

10.5 Explainability and auditability

A model may provide a useful prediction without providing a sufficiently understandable reason. Yet accounting and auditing require evidence and traceability. Explainability should therefore be treated as a practical control requirement where AI outputs affect material decisions, not as a purely academic property.

10.6 Generative AI inaccuracies

Generative AI can produce fluent but unsupported statements. In an accounting setting this may take the form of a wrong standard reference, a fabricated citation or an incorrect interpretation of a transaction. The risk is amplified because the output can look professional. The appropriate response is not to reject the technology but to establish verification routines, approved knowledge sources and clear rules about when human review is mandatory.

10.7 Automation bias and deskilling

When AI performs routine decisions successfully, users may become less likely to question it. Over time, heavy reliance can also weaken the skills needed to detect when the system is wrong. Kokina et al. (2025) explicitly identify overreliance as a challenge in audit adoption. Critical thinking and professional scepticism must therefore be preserved through training, review procedures and exposure to non-routine cases.

10.8 Accountability and regulatory uncertainty

AI can contribute to a decision without being a legal or professional decision-maker. Accountability must therefore remain clearly assigned to human roles and institutions. In India, RBI's FREE-AI framework and SEBI's responsible-use initiative show the direction of travel: innovation is being accompanied by stronger attention to governance, risk and responsibility (RBI, 2025; SEBI, 2025).

11 Transformation of the accounting and finance profession

The strongest conclusion from the literature is not that accountants will disappear, but that the composition of accounting work will change. Routine processing is easier to automate than interpretation, negotiation, ethical reasoning and accountability. Abbas (2026) notes that digital technologies can reshape management accountants' roles through automation, upskilling, deskilling and reskilling, while Vitali and Giuliani (2024) show that digitalisation can also influence organisational structures and hiring patterns in audit firms.

This change can be represented as a movement from a transaction-centred role toward an exception- and insight-centred role. In a traditional workflow, a professional may spend substantial time collecting records, checking routine entries and preparing recurring reports. In an AI-enabled workflow, more time can be spent challenging anomalies, interpreting trends, explaining results to management and governing the systems that produce financial information.

ACCA's 2025 and 2026 professional research similarly places AI, data and technology alongside ethics and strategic capability in the future role of accountants (ACCA, 2025a, 2025b; ACCA & CA ANZ, 2026). ICAI's expansion of AI certification activity further indicates that technological competence is becoming part of professional development in India (ICAI, 2026).

12 Skills required for AI-enabled accounting and finance

The future skill set is hybrid. Technical accounting knowledge remains the foundation, but it must be combined with the ability to work with data and AI systems. Five capability groups are particularly important.

Table 2 presents the skills required for AI-enabled accounting and finance.

Table 2. Skills required for AI-enabled accounting and finance.

Capability group	Examples	Why it matters
Accounting expertise	Standards, reporting, tax, audit, controls	Defines what a correct financial result should mean.
Data and AI literacy	Data quality, model basics, prompt evaluation, AI limitations	Allows professionals to use and challenge AI tools.
Analytical judgement	Risk assessment, scenario analysis, interpretation	Converts AI output into a context-sensitive decision.
Governance and ethics	Privacy, accountability, explainability, professional scepticism	Protects trust and ensures responsible use.
Human capabilities	Communication, storytelling, collaboration, leadership	Turns analysis into action across the organisation.

The implication for education is clear. AI should not be taught as a substitute for accounting fundamentals. Students and professionals need to understand both the financial logic of a problem and the behaviour of the technology used to address it. This supports the shift from tool training toward digital-professional competence.

13 Indian context: Professional and regulatory developments

India offers a useful setting for observing the institutionalisation of AI in accounting and finance. ICAI has created an AI-focused committee and has expanded its professional AI education, including AICA certification levels. ICAI's 2026 AI summit also included an advanced AICA Level 3 programme and the publication 'AI Essentials for Chartered Accountants' (ICAI, 2026). These developments signal that AI capability is moving into the mainstream of professional accountancy development.

RBI's FREE-AI initiative provides a regulatory perspective. The August 2025 report on responsible and ethical enablement of AI in the financial sector reflects the need to balance innovation with concerns such as transparency, fairness, accountability, privacy and security. RBI has also reported the piloting of MuleHunter.AI for detecting potential mule bank accounts (RBI, 2025).

SEBI's June 2025 consultation paper on responsible use of AI/ML in securities markets similarly shows a movement toward explicit governance expectations. The proposal recognised that AI can support activities such as compliance, surveillance and cybersecurity while suggesting a differentiated regulatory approach based on the nature and impact of the use case (SEBI, 2025).

These developments suggest that India is moving toward a model in which professional competence, institutional accountability and technological innovation have to develop together. For accounting researchers, this creates an important opportunity to examine how regulation and professional education shape AI adoption rather than treating adoption as purely a technical decision.

14 Proposed human-centred AI transformation model

Based on the literature, this paper proposes a five-stage model. The first stage is AI capability: the availability of machine learning, NLP, Generative AI, RPA, OCR and explainability tools. The second is functional use: where these capabilities are embedded in accounting, audit, finance or compliance tasks. The third is process outcome: speed, consistency, prediction, anomaly identification and improved attention to exceptions. The fourth is professional transformation: routine work is reduced

and analytical, advisory and governance responsibilities expand. The fifth is organisational value: better insight, stronger risk visibility, greater responsiveness and more strategic capacity.

The model also places governance and capability safeguards underneath the entire chain. This reflects a central finding of the literature: AI value is conditional (Figure 1). Data quality, privacy, cybersecurity, explainability, human oversight, AI literacy, performance monitoring and accountability determine whether the movement from capability to value is reliable. In other words, governance is not a separate compliance activity added after implementation; it is part of the value-creation mechanism itself.

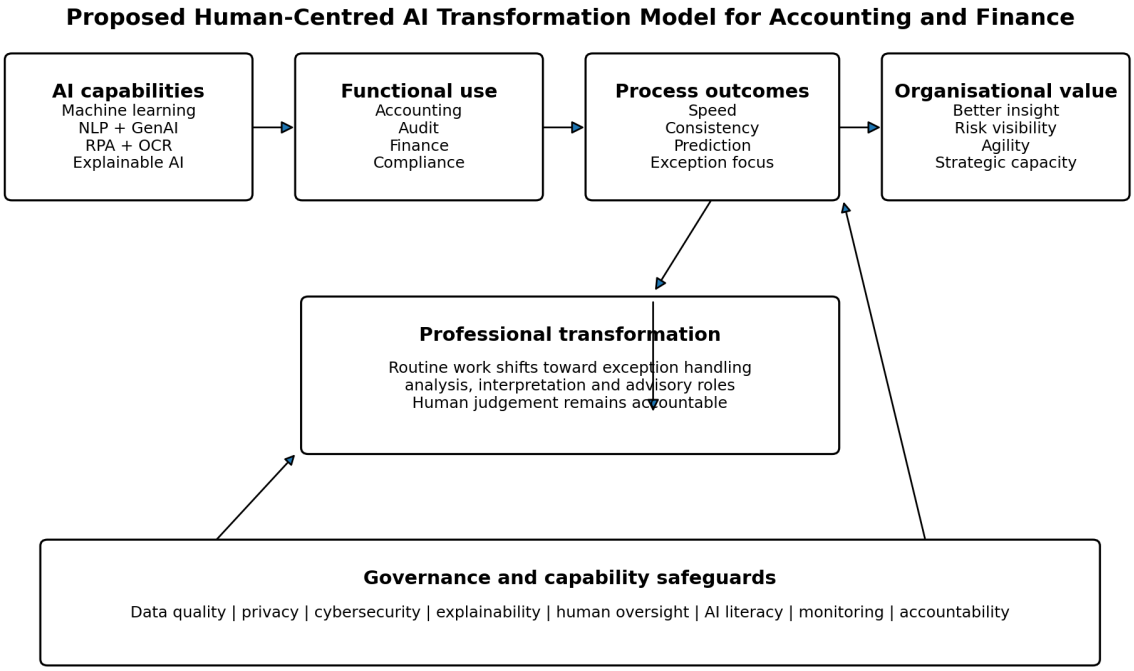


Figure 1. Proposed human-centred AI transformation model for accounting and finance.

The proposed framework differs from a purely technology-centred model because it treats professional integration as an intermediate outcome. An AI tool that improves processing speed but leaves users unable to validate outputs may create operational efficiency while increasing decision risk. Conversely, an AI system that is slightly slower but highly auditable may produce greater net value in a regulated process. This makes governance quality a strategic variable rather than only a constraint.

15 Research propositions for future empirical testing

The conceptual model leads to the following propositions. They are presented for future empirical testing and are not claimed as statistically established findings in this paper.

- **P1:** AI capability maturity is positively associated with the efficiency of accounting and finance processes when the selected use case is suitable for automation or analytical augmentation.
- **P2:** Data quality strengthens the relationship between AI capability and the reliability of accounting and financial outputs.

- **P3:** AI literacy among accounting and finance professionals strengthens the relationship between AI adoption and decision usefulness.
- **P4:** Human oversight and explainability strengthen trust in AI-assisted accounting and finance decisions.
- **P5:** Stronger AI governance reduces the risk that efficiency gains from automation will be accompanied by higher control, privacy or accountability risks.
- **P6:** A human-augmentation orientation is positively associated with the expansion of strategic and advisory work among accounting and finance professionals.

16 Discussion

The synthesis supports a shift from an automation narrative to an augmentation narrative. Automation remains important, especially for high-volume and rule-intensive tasks, but it is only the first layer of transformation. The larger organisational opportunity comes from using the capacity released by automation to improve interpretation, monitoring and strategic decision support.

A second insight is that not all AI use cases should be treated equally. Low-risk productivity uses, such as document summarisation or routine classification with human checking, can tolerate different control arrangements from high-impact uses, such as credit decisions, material financial reporting judgements or fraud escalations. Governance should therefore be proportionate to the consequence of error. This aligns with the tiered logic visible in SEBI's 2025 consultation approach and with professional emphasis on AI assessment and assurance (ACCA, 2025b; SEBI, 2025).

A third insight is that data foundations matter as much as algorithms. ACCA and CA ANZ's 2026 research reports data quality problems, skills gaps and difficulty integrating multiple data sources as major barriers for AI-enabled finance. The implication for accounting departments is practical: before investing heavily in advanced AI, organisations should improve data definitions, ownership, controls, lineage and accessibility.

A fourth insight concerns professional identity. If accountants define their value only in terms of producing standard reports, AI will appear mainly as a substitute. If their value is defined more broadly around assurance, interpretation, ethics, governance and business understanding, AI becomes a capability multiplier. This is consistent with the professional direction described by ACCA and the skills investments being made by ICAI.

17 Managerial and professional implications

1. Start with high-value problems, not with technology. Map the workflow, identify bottlenecks and determine where AI can safely create additional capacity.
2. Create explicit decision rights. For each AI-assisted task, specify who reviews the output, who can override it and who remains accountable.
3. Treat data as a control asset. Establish ownership, quality checks, lineage and access rules before scaling AI.
4. Introduce AI assurance activities. Test accuracy, bias, robustness and explainability periodically rather than only at initial deployment.
5. Build formal learning pathways. Combine AI literacy with accounting standards, professional ethics, data skills and critical judgement.

6. Measure value beyond cost savings. Use indicators such as cycle time, exception resolution, forecast usefulness, error rates, control quality and stakeholder trust.

18 Limitations

This study has three main limitations. First, it is a literature-based conceptual paper and does not test the proposed propositions with primary data. Second, AI evolves rapidly, so particular tools and implementation practices may change faster than conventional accounting technologies. Third, the literature is dispersed across disciplines, and differences in research settings mean that findings cannot always be compared directly. These limitations do not invalidate the framework, but they indicate the need for empirical validation.

19 Future research directions

Future research can test the proposed framework using survey, case-study and experimental designs. In India, a multi-group survey of Chartered Accountants, auditors, management accountants and finance managers could examine whether AI literacy, data quality and governance explain differences in perceived AI value. Experimental studies could compare human-only, AI-only and human-AI decision conditions for selected accounting tasks. Case studies could examine how audit firms and finance departments redesign roles after Generative AI adoption. Another promising area is AI assurance: researchers can investigate whether structured AI assessments improve confidence in financial outputs and reduce overreliance.

Research should also examine inclusion. Smaller accounting practices and smaller financial institutions may not have the same data, technology or specialist resources as large organisations. The future of AI-enabled finance should therefore not be evaluated only through the experience of highly resourced organisations. Accessibility, cost and capability building are relevant to inclusive digital transformation.

20 Conclusion

Artificial Intelligence is becoming a catalyst for structural change in accounting and finance. Its significance lies not only in automating repetitive activities but in extending the capacity of financial professionals to analyse information, identify risk, generate scenarios and support decisions. The literature reviewed in this paper shows that AI is already relevant to transaction processing, audit, fraud detection, forecasting, credit, investment analysis, customer service and compliance.

At the same time, the evidence does not justify a technology-first view of transformation. AI can create value only when its outputs are supported by reliable data, appropriate process design, capable users and strong governance. Privacy, cybersecurity, bias, explainability, model reliability, generative-AI inaccuracies and automation bias are not secondary issues. They directly affect whether an AI-enabled process can be trusted.

The paper therefore proposes a human-centred view of AI transformation. AI should handle what machines handle well: high-volume processing, pattern detection, continuous monitoring and rapid retrieval. Professionals should retain what people are accountable for: judgement, challenge, ethical reasoning, context and final responsibility. The organisational objective is not to maximise automation. It is to maximise trustworthy financial insight.

For India, the direction is especially relevant. ICAI's AI initiatives, RBI's FREE-AI framework and SEBI's responsible-use approach indicate that the ecosystem is moving toward a model in which innovation and accountability develop together. The central policy and managerial challenge is therefore to build institutions in which technology amplifies professional competence rather than weakening it.

The future accountant or finance professional is consequently best understood not as a replacement for AI, nor as a passive user of AI, but as a professional who can work with intelligent systems while remaining capable of questioning them. That combination of accounting expertise, AI literacy, critical judgement and governance capability is likely to define the next stage of the profession.

21 AI assistance disclosure

Generative AI tools were used to support language drafting and document formatting during preparation of this manuscript. The content was reviewed and edited for accuracy, the cited sources were checked against authoritative or scholarly records, and the author takes responsibility for the final manuscript and its interpretation.

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