

Artificial Intelligence in Accounting and Auditing: Evidence, Professional Judgment, Adoption, Governance, And Financial Reporting

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Abstract

Artificial Intelligence (AI), machine learning (ML), Generative Artificial Intelligence (GenAI), and Large Language Models (LLMs) are reshaping accounting and auditing by changing how financial information is processed, analysed, documented, interpreted, and assured. This article presents a structured integrative literature review of recent research on AI in accounting and auditing, with emphasis on AI adoption, accounting efficiency, audit quality, financial reporting, professional judgement, human–AI collaboration, and governance. The review synthesises peer-reviewed empirical studies, systematic reviews, conceptual research, and selected authoritative professional research available through August 2026. The evidence indicates that AI can improve productivity, automate repetitive activities, expand analytical coverage, support anomaly detection, and accelerate reporting processes. Recent field evidence shows that GenAI can reallocate accountants' time from routine data-entry activities toward communication and quality assurance, while corporate-disclosure research documents measurable GenAI use in financial-report writing. At the same time, the literature identifies important risks relating to inaccurate outputs, over-reliance, algorithmic bias, data privacy, explainability, cybersecurity, model reliability, and accountability. The synthesis supports an augmentation or complementarity perspective rather than a simple substitution model: AI creates the greatest value when combined with accounting expertise, professional scepticism, human validation, and effective governance. The review identifies important gaps concerning human–AI collaboration, professional judgement, AI competency, SMEs, emerging economies, long-term outcomes, and the distinction between traditional AI and GenAI. The article concludes that the future of accounting depends not only on technological adoption but also on the development of responsible human–AI systems that preserve professional accountability and trust in financial information.

Keywords: Artificial Intelligence; Generative AI; Accounting; Auditing; Professional Judgement; Financial Reporting; AI Adoption; AI Governance; Human–AI Collaboration; Machine Learning

1. Introduction

Artificial Intelligence has become an important technological force in the accounting and auditing profession. Earlier accounting automation concentrated mainly on predefined rules, transaction processing, and repetitive activities. Contemporary AI systems extend this logic by identifying patterns in large datasets, producing predictions, analysing unstructured information, generating natural-language content, and assisting professional decision-making. As a result, AI is no longer confined to back-office processing; it increasingly influences auditing, financial reporting, management accounting, taxation, fraud detection, forecasting, and accounting information systems (Abdo-Salloum & Chehade, 2026; Jones & Free, 2026).

The accounting profession is particularly relevant to this transformation because accounting work is built around information processing and professional judgement. Transactions must be classified, records reconciled, estimates developed, evidence evaluated, disclosures prepared, and conclusions communicated to users. AI can perform or support many of these activities at scale. Yet the credibility of accounting information also depends on professional scepticism, ethical reasoning, contextual interpretation, and accountability. This creates a central tension: greater automation can increase efficiency, but insufficient human oversight may introduce errors or weaken professional responsibility.

Recent research provides strong evidence that the issue is no longer hypothetical. Choi and Xie (2026) combine survey evidence from 277 professional accountants with proprietary transaction-level data from an AI-enabled platform serving 79 small and medium-sized enterprises (SMEs). They report substantial heterogeneity in GenAI adoption and find evidence of productivity gains and a shift in accountants' effort from routine data-entry activities toward communication and quality assurance. Their results also suggest that accountants intervene selectively when AI confidence is lower, pointing to human–AI complementarity rather than simple substitution (Choi & Xie, 2026).

AI is also entering the financial-reporting process itself. Blankespoor, deHaan, and Li (2026) analyse corporate earnings press releases, conference-call prepared remarks, risk factors, MD&A sections, and IPO filings through 2024. They identify statistically significant GenAI use across all five disclosure categories and estimate that up to 4.5% of new text was written by GenAI in 2024 in the settings examined. This evidence shows that GenAI is moving from experimentation towards observable use in financial communication.

In auditing, Kokina et al. (2025) report evidence from 22 interviews with experienced audit professionals. Their findings indicate that relatively simple AI applications, such as document data extraction and optical character recognition, are already widely used, whereas more complex AI tools are still developing. They identify transparency and explainability, bias, data privacy, robustness and reliability, fear of auditor over-reliance, and the need for guidance as major challenges.

Against this background, the purpose of this article is to integrate the recent literature and examine AI in accounting and auditing through five interconnected dimensions: adoption, accounting and audit outcomes, professional judgement, governance, and financial reporting. The article addresses five research questions.

1. How is AI transforming contemporary accounting and auditing practices?
2. What empirical evidence exists regarding AI adoption and its relationship with accounting efficiency, audit quality, and financial reporting?
3. How does AI affect professional judgement and the role of accountants and auditors?
4. What governance, ethical, and professional risks arise from AI adoption?
5. What research gaps remain for future empirical investigation?

2. Literature Review

2.1 Evolution of AI in Accounting

The literature has evolved from early rule-based and expert-system applications toward RPA, predictive analytics, ML, NLP, GenAI, and LLMs. The shift matters because newer technologies can work with both structured and unstructured data and can generate rather than merely retrieve content. Abdo-Salloum and Chehade (2026), using a PRISMA-guided systematic review of 31 studies published from 2021 to 2025, report that AI is associated with operational efficiency, financial-reporting credibility, routine-task automation, and fraud-detection capabilities, while adoption continues to face ethical, organisational, educational, and regulatory barriers.

Jones and Free (2026) extend this literature by treating AI and ML as technologies that alter the evidentiary foundations of accounting judgement. Their review spans auditing, financial reporting, management accounting, taxation, ESG, financial distress, earnings forecasting, and public-sector analytics. They argue that AI expands the types of evidence available to accountants and that professionals increasingly need to interpret, validate, and govern AI outputs rather than generate every prediction themselves. This perspective is useful because it reframes AI from a narrow automation tool to a technology that can change professional authority.

2.2 AI Adoption in Accounting and Auditing

AI adoption is shaped by more than technological availability. Research using integrated adoption models indicates that competitive pressure, vendor ecosystems, top-management support, relative advantage, AI readiness, innovation climate, perceived usefulness, and data governance influence implementation. In a study of accounting and auditing firms, a validated TOE–TAM–RDT model showed that adoption was associated with financial reporting accuracy and auditing efficiency and that data governance strengthened these benefits (Does AI Adoption..., 2025).

The adoption literature therefore supports a socio-technical view. Organisational readiness, financial resources, infrastructure, employee capability, trust, and governance conditions all affect whether AI systems are actually used and whether their use produces value.

2.3 AI and Accounting Efficiency

Efficiency is one of the most consistently reported benefits of AI. Applications include transaction classification, invoice processing, reconciliation, data extraction, document review, forecasting, and routine reporting. Choi and Xie (2026) provide unusually detailed field evidence showing that GenAI adoption can increase productivity and change the composition of accountants' work. The key implication is not simply that less work is required, but that the balance of work can move from mechanical processing towards communication and quality assurance.

At the same time, efficiency cannot be equated with automatic reliability. When users rely on AI recommendations that conflict with professional expectations, error risk can increase. The literature therefore points toward AI-assisted efficiency under human review rather than autonomous accounting.

2.4 AI and Auditing

AI is increasingly applied to audit planning, risk assessment, anomaly detection, fraud detection, document analysis, continuous auditing, transaction testing, and population-level analysis. These applications can expand the volume of evidence that auditors can examine and can make risk identification more timely.

Kokina et al. (2025) show, however, that implementation differs by task complexity. Simple extraction and OCR applications are relatively mature, while complex AI applications remain less developed. The field evidence highlights explainability, privacy, bias, reliability, and auditor over-reliance as material constraints. Thus, the literature supports AI as an analytical capability that complements rather than removes auditor responsibility.

2.5 AI and Audit Quality

Empirical studies generally report a positive association between AI adoption and audit-related outcomes, although causal interpretation remains difficult. Khan, Jan, and Zia-ul-Haq (2025) analyse 2,912 non-financial firm-year observations from GCC markets for 2010–2023 and find that AI adoption is positively associated with integrated financial reporting; the positive relationship is stronger when audit quality is higher, particularly for firms with specialised auditors and higher audit fees and without restatements.

This evidence suggests a mechanism in which AI improves information processing and interacts with audit quality and governance to influence reporting outcomes. However, firms that adopt AI may also have stronger controls and technology capabilities before adoption, making longitudinal and quasi-experimental research desirable.

2.6 AI and Financial Reporting

AI is entering both the production and communication of financial information. Traditional analytics focused on analysis of existing records; GenAI adds the ability to draft narrative disclosure and other textual content. Blankespoor et al. (2026) provide direct evidence of GenAI use in corporate disclosures and show that AI-generated text has systematically different linguistic properties.

This development creates benefits in drafting speed, information extraction, readability, and consistency, but also raises questions about accuracy, disclosure bias, accountability, consistency with underlying accounting records, and investor interpretation. Financial-reporting research must therefore examine not only efficiency but also the reliability and governance of AI-assisted disclosure.

2.7 AI and Professional Judgement

Professional judgement is central to accounting and auditing because many decisions require interpretation of standards, uncertainty, contextual knowledge, and ethical evaluation. Jones and Free (2026) argue that AI changes the source of evidence available to professionals and therefore changes the nature of professional judgement. When algorithms outperform traditional approaches in predictive tasks, accountants may become less like sole producers of estimates and more like evaluators of machine-generated evidence.

The emerging model can be described as hybrid intelligence: data are analysed by an AI system, recommendations are produced, and the professional then evaluates, validates, contextualises, and accepts or overrides the output. This model is increasingly consistent with the empirical evidence on selective human intervention.

2.8 Human–AI Collaboration and the Changing Accountant

The reviewed literature increasingly rejects a simple human-versus-machine framing. AI is particularly suited to repetitive processing, large-scale pattern recognition, anomaly detection, and information extraction. Human professionals remain essential for contextual interpretation, professional scepticism, ethical reasoning, exception handling, and accountability.

This shift suggests a new competency profile for accountants: accounting knowledge must be combined with AI literacy, data interpretation, prompt formulation, output verification, risk awareness, and governance skills. The profession is therefore changing not only because tasks are automated but because the boundary between technological and professional work is being redrawn.

2.9 AI Governance and Ethical Issues

Governance is a cross-cutting issue in the literature. Major concerns include inaccurate outputs, hallucinations, algorithmic bias, privacy, cybersecurity, lack of explainability, model instability, over-reliance, deskilling, and accountability. Kokina et al. (2025) identify explainability, bias, privacy, robustness and auditor over-reliance as significant audit challenges. Abdo-Salloum and Chehade (2026) additionally highlight cost, job security, educational readiness, and uneven adoption across regions.

For accounting organisations, responsible AI use therefore requires policies defining permitted uses, confidential-data restrictions, human-review requirements, documentation, validation, escalation, and responsibility. Governance should be integrated with internal control and professional risk management rather than treated as a separate technology issue.

3. Methodology

3.1 Research Design

This study adopts a structured integrative literature-review design. The objective is to synthesise recent evidence on AI in accounting and auditing, identify convergent and divergent findings, and derive a research agenda. The study is not presented as a primary empirical survey and therefore does not generate new respondent-level statistics or regression estimates.

3.2 Literature Scope and Source Selection

The review prioritised peer-reviewed journal articles, systematic reviews, empirical archival studies, field studies, conceptual reviews, and selected authoritative professional research available through August 2026. Particular emphasis was placed on 2025–2026 publications because GenAI and LLM-based applications are evolving rapidly. The review deliberately combines different methodological traditions because the topic spans organisational adoption, archival accounting outcomes, audit practice, professional judgement, and technology governance.

The core evidence base includes recent studies from the Journal of Accounting Research, Journal of Accounting Literature, International Journal of Accounting Information Systems, Asian Review of Accounting, SAGE Open, and Computers in Human Behavior Reports, together with the Institute of Chartered Accountants of Scotland report on GenAI and professional judgement. The selection was designed to balance established accounting scholarship with recent interdisciplinary and professional evidence.

3.3 Analytical Procedure

Each selected study was classified according to author and year, country or context, sample or data source, methodology, AI application, key findings, and reported limitations. The extracted evidence was then compared across seven themes: AI adoption, accounting efficiency, auditing, financial reporting, professional judgement, human–AI collaboration, and governance. The resulting evidence matrix is presented in Table 1.

The Results section reports patterns emerging from the reviewed studies. Where a study contains quantitative estimates, those estimates are described as findings of the original study rather than as statistical results generated by the present article. This distinction maintains methodological consistency and prevents fabrication of primary-data results.

3.4 Methodological Limitation

Because the study is an integrative review rather than a statistical meta-analysis, effect sizes are not pooled. Differences in country, sample, research design, technology type, measurement, and adoption maturity limit direct numerical comparison across studies. In addition, the GenAI literature is relatively new, so many long-run outcomes remain uncertain.

Table 1. Summary of Reviewed Studies on AI in Accounting and Auditing

Author(s) / Year	Country / Context	Sample Data	Methodology	AI Application	Key Findings	Research Limitations
Kokina, Blanchette, Davenport & Pachamanova (2025)	Large public accounting firms / audit practice	22 experienced audit professionals	Qualitative field study; semi-structured interviews	AI in auditing; data extraction; OCR; RPA; ML; NLP	Simple AI is widely used; complex AI is still developing. Major concerns: explainability, bias, privacy, reliability, over-reliance, and guidance.	Confidential interview data; qualitative design limits statistical generalisation.
Khan, Jan & Zia-ul-Haq (2025)	GCC listed firms	2,912 non-financial firm-year observations, 2010–2023	Panel OLS with propensity-score matching robustness	AI adoption, audit quality, integrated financial reporting	AI adoption is positively associated with integrated financial reporting; stronger audit quality strengthens the relationship.	Geographically bounded to GCC markets; archival measures limit direct inference about individual professionals.
Jones & Free (2026)	International accounting literature	Published literature across several accounting domains	Conceptual and integrative literature review	AI/ML in auditing, reporting, management accounting, tax, ESG, prediction	ML can outperform traditional statistical approaches in prediction-intensive settings; AI expands the evidence base and shifts accountants toward interpretation, validation, and governance.	Review-based evidence; rapidly changing technology requires continuing updates.

Author(s) / Year	Country / Context	Sample Data	Methodology	AI Application	Key Findings	Research Limitations
Choi & Xie (2026)	U.S.-linked accounting technology platform / SMEs	277 professional accountants; 79 SMEs; >200,000 transactions	Survey plus proprietary field data and task-level analysis	Generative AI in accounting; human-AI collaboration	GenAI is associated with productivity gains, reallocation from routine data entry to communication/quality assurance, and faster month-end closing. Human intervention remains important when AI confidence is low.	Proprietary data may restrict replication; evidence reflects early-stage GenAI adoption.
Blankespoor, deHaan & Li (2026)	Publicly reporting firms / U.S. market	Corporate disclosures through 2024; earnings releases, prepared remarks, risk factors, MD&A, IPO filings	Large-scale archival textual analysis	GenAI in financial-report writing	Statistically significant GenAI use appears across five disclosure types; up to 4.5% of new text was written by GenAI in 2024 in the examined settings.	Actual internal AI-use processes are not observed directly; causal interpretation is limited.
Abdo-Salloum & Chehade (2026)	International literature	31 studies selected from an initial 41 records	PRISMA-guided systematic review; searches in Google Scholar, Scopus, Web of Science and ScienceDirect	AI in accounting/auditing; fraud detection; financial reporting; adoption	AI is associated with efficiency, reporting credibility, automation and fraud detection, while ethical, organisational, regulatory and educational barriers remain.	Review depends on available literature; search period ends in May 2025.
Chai, Nicholson, Salijeni, Sokolovsky & Chahed (2026)	Mid-tier accounting practice / UK professional context	Commissioned professional case evidence; 18-page report	Case-based professional research with interviews, survey and case evidence reported by ICAS	GenAI and professional judgement	The study highlights task acceleration alongside concerns about error, privacy, confidentiality and the continuing need for human judgement.	Commissioned professional research; context-specific and not intended as a representative population study.

Source note. Author's synthesis of the reviewed literature. The table classifies studies by methodological design and does not imply that the present article collected the underlying primary data.

4. Results

4.1 AI Adoption Is Expanding but Remains Uneven

The evidence indicates that AI adoption is increasing across accounting and auditing, but adoption intensity varies by task, organisation, technology maturity, and professional context. Simple, structured applications are generally more mature than complex judgement-intensive systems. Adoption is shaped by technological readiness, management support, vendor ecosystems, financial resources, perceived usefulness, trust, employee capability, and governance conditions. The review therefore supports a socio-technical rather than purely technological explanation of AI adoption.

4.2 AI Is Associated with Accounting Productivity and Process Efficiency

The reviewed empirical evidence supports a positive association between GenAI use and accounting productivity, particularly for routine and data-intensive activities. Choi and Xie (2026) report a reallocation of accountants' effort away from routine data entry towards communication and quality assurance, alongside faster month-end closing and more granular ledgers. These findings suggest that AI may change the composition of accounting work, not merely reduce workload. However, the same evidence shows why human review remains necessary.

4.3 AI Expands Audit Analytics but Does Not Eliminate Auditor Responsibility

AI applications in auditing improve the ability to process large populations, identify anomalies, extract evidence, and support risk assessment. Yet Kokina et al. (2025) show that complex AI use remains less mature and that explainability, privacy, bias, reliability, and over-reliance are significant barriers. The literature therefore supports AI as an enhancement of audit capacity rather than a substitute for auditor responsibility.

4.4 AI Is Becoming Embedded in Financial Reporting

The evidence shows that GenAI is already present in corporate financial-reporting processes. Choi and Xie (2026) find changes in accounting records and closing processes, while Blankespoor et al. (2026) document measurable GenAI use in corporate disclosure writing. Financial reporting is thus becoming a key area for research on AI-generated information, including accuracy, readability, consistency, accountability, and investor interpretation.

4.5 Professional Judgement Remains a Core Control Mechanism

The review finds that AI changes the location and nature of judgement rather than making judgement irrelevant. Professionals must increasingly determine whether AI outputs are reasonable, supported by reliable data, consistent with standards, and appropriate to the circumstances. Jones and Free (2026) describe this movement as a shift toward interpreting, validating, and governing AI outputs.

4.6 The Evidence Supports Human–AI Complementarity

Across the reviewed studies, a consistent pattern emerges: AI performs relatively well on repetitive processing, pattern detection, information extraction, and prediction, while humans remain central to contextual interpretation, ethical reasoning, professional scepticism, exception handling, and accountability. The resulting model is better described as human–AI complementarity than complete substitution.

4.7 Governance Is a Necessary Condition for Sustainable AI Use

Governance risks appear across virtually all reviewed themes. Accuracy, hallucination, privacy, bias, explainability, cybersecurity, over-reliance, model instability, and accountability can weaken the value created by AI. Therefore, the benefits of AI are best understood as conditional on competent human use and effective governance rather than as automatic consequences of technology adoption.

5. Discussion

5.1 From Automation to Augmentation

The central pattern in the literature is a movement from task automation toward professional augmentation. AI reduces the amount of time devoted to routine processing, but it simultaneously creates more work in verification, exception

handling, and interpretation. This implies that the future value of accounting professionals may depend less on the ability to execute repetitive processes and more on the ability to supervise and interpret intelligent systems.

5.2 Professional Judgement and Epistemic Authority

AI and ML introduce a new source of evidence into accounting. When an algorithm detects fraud risk, predicts financial distress, or generates a reporting recommendation, the professional must determine whether the evidence is credible and how it should influence the final conclusion. Jones and Free (2026) argue that this changes the profession's epistemic foundations. The key issue is therefore not whether the machine is intelligent, but how machine-generated evidence is validated and incorporated into professional judgement.

5.3 Financial Reporting and Accountability

The increasing use of GenAI in disclosures introduces a new accountability problem. The person who signs or approves a financial report remains responsible for the reported information even when AI has contributed to its preparation. Governance frameworks should therefore distinguish between assistance and accountability: AI can assist with drafting and analysis, but human professionals must retain responsibility for validation and approval.

5.4 Audit Quality and the Human Control Layer

The evidence on audit quality is encouraging but should not be interpreted as evidence for unrestricted automation. AI can expand coverage and identify patterns that are difficult to detect manually, yet the auditor remains responsible for evaluating evidence. The effective system is therefore a layered architecture: automated detection followed by human assessment, documentation, and conclusion.

5.5 Implications for Accounting Education

Accounting education needs to evolve from technology awareness to AI-enabled professional competence. Important capabilities include AI literacy, data interpretation, prompt formulation, critical evaluation of outputs, professional scepticism, privacy awareness, ethics, and model governance. Students should learn how to use AI while also learning when not to trust it.

5.6 Implications for Accounting Organisations and Regulators

Organisations adopting AI should establish clear rules for confidential data, approved tools, human review, validation, documentation, escalation of errors, and responsibility. Professional bodies and regulators should provide guidance on AI-assisted evidence, disclosure preparation, audit documentation, confidentiality, and accountability. Governance is most effective when embedded in internal control and quality-management systems.

Table 2. Research Gaps and Directions for Future Research

Research gap	Evidence from reviewed literature	Suggested future research
Human–AI collaboration	Recent field evidence suggests complementarity, but the conditions under which human expertise improves AI outcomes remain insufficiently tested.	Use experiments, task-level field studies, or longitudinal designs to examine when professionals accept, modify, or override AI outputs.
Professional judgement	AI changes the source of evidence and may influence professional scepticism and ethical decisions.	Measure AI influence on judgement, scepticism, override behaviour, and accountability.
AI competency	Studies stress skills and training, but fewer studies directly test whether AI competency improves accounting outcomes.	Develop and validate an AI-competency scale for accountants and auditors and test moderation/mediation effects.

Research gap	Evidence from reviewed literature	Suggested future research
SMEs and smaller practices	Large firms and technology platforms are more visible in the recent evidence than small practices.	Study cost, readiness, infrastructure, privacy, training, and vendor dependence in SMEs.
Emerging economies	Available evidence includes GCC markets and selected international studies, but country-level evidence remains uneven.	Conduct empirical studies in India and other emerging economies.
Traditional AI versus GenAI	AI is often treated as a broad umbrella term despite differences in RPA, ML, predictive analytics, and GenAI.	Use technology-specific constructs and compare their effects on efficiency, quality, judgement, and risk.
Long-term effects	Most GenAI evidence is recent and reflects early-stage adoption.	Use longitudinal data to examine productivity, skill changes, reporting quality, and occupational transformation.
Governance and accountability	Explainability, privacy, bias, reliability, and responsibility remain recurring concerns.	Develop tested AI-governance frameworks linked to internal controls, audit quality, and professional standards.

6. Conclusion

The literature reviewed in this article indicates that AI is transforming accounting and auditing at both the task level and the professional level. AI can automate repetitive work, increase analytical coverage, support anomaly detection, improve process efficiency, and contribute to financial-reporting and audit outcomes. Recent evidence also shows that GenAI has begun to enter actual accounting workflows and corporate financial disclosures.

At the same time, the review does not support the view that AI can independently replace professional accountants and auditors. Instead, the evidence points towards a human–AI complementarity model. AI is strongest where tasks are repetitive, data-intensive, and predictive; human professionals remain essential where decisions require contextual interpretation, scepticism, ethical reasoning, and accountability.

The most important implication is that AI adoption should be evaluated together with professional competence and governance. Reliable AI-enabled accounting requires accurate data, appropriate system design, competent users, human validation, confidentiality controls, and explicit accountability. Without these elements, technology may accelerate processes without improving the quality or trustworthiness of the resulting information.

The review identifies a clear agenda for future research: empirically test human–AI collaboration, examine professional judgement and AI competency, expand evidence from SMEs and emerging economies such as India, distinguish traditional AI from GenAI, and develop longitudinal evidence on financial reporting, audit quality, skills, and employment. These areas offer a strong basis for a future empirical study in Commerce and Accounting that links AI adoption with accounting efficiency, financial reporting quality, professional judgement, and governance.

Overall, the future of accounting should not be framed as human versus AI. The more defensible conclusion from the current evidence is human with AI: technology provides scale and computational power, while accounting professionals provide context, scepticism, ethics, and accountability. The long-term value of AI in accounting will therefore depend on the profession’s ability to integrate technological capability with enduring principles of reliability, transparency, and professional responsibility.

7. Proposed Conceptual Framework for Future Empirical Research

Based on the synthesis, a future empirical study can test an integrated model in which organisational readiness, management support, technology readiness, trust, and data quality influence AI adoption. AI adoption is then expected to improve accounting process efficiency, which may influence financial reporting quality and audit quality. AI competency and professional judgement can be specified as moderators, while governance can be treated as a cross-cutting condition that strengthens the reliability of AI-enabled processes.

Organisational Readiness + Management Support + Technology Readiness + Trust + Data Quality

↓

AI Adoption

↓

Accounting Process Efficiency

↓

Financial Reporting Quality / Audit Quality

Moderating or conditioning variables: AI Competency, Professional Judgement, and Governance.

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Evidence verification note. The recent literature listed above was checked against publisher or institutional records during preparation of this manuscript. The article deliberately distinguishes findings of the cited studies from the Results of the present literature synthesis.