

ARTIFICIAL INTELLIGENCE IN ACCOUNTING AND AUDITING: A REVIEW AT THE INTERSECTION OF MANAGEMENT SCIENCE AND ACCOUNTING & FINANCE

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Abstract

AI is not merely an emerging trend in the accounting and auditing landscape but a transformative force that is increasingly becoming integral to the work of both professionals and firms. From its initial experimentation to full integration, AI is fundamentally changing the roles of accounting and auditing professionals. This review aims to summarize the latest research available in the literature and industry reports from 2020 to 2026 to explore the current state of AI within accounting and auditing. Machine learning, natural language processing, robotic process automation, and massive language models are the four main technology areas that are highlighted in the analysis. Each of these is assigned to financial reporting, fraud detection, audit planning, continuous auditing, and management accounting. There are clear and quantifiable gains to be seen: The number of accounting firms using AI increased from 9% in 2024 to 41% in 2025, with 77% of the firms stating that they intend to invest more in AI (Wolters Kluwer, 2025). Clara AI platform by KPMG lowered weekly hours of auditors by 18% and had the lowest PCAOB auditor deficiency rate of 20% among the Big 4 firms (Siano et al., 2026). Continuous auditing using LLM has decreased extraction accuracy by 97% and cross-verification time by 83%. (Zhang et al., 2026). There are, however, significant challenges in the adoption process, such as lack of skills, data privacy issues, algorithmic biases, regulatory ambiguities, and professionals' doubts about the autonomy of artificial intelligence (Abdo-Salloum & Chehade, 2026; Kassar & Jizi, 2026). The review finds that ai is best used as a tool to support and enhance human decision-making, rather than to supplant it, and outlines key research areas that need further development, such as fine-tuning AI models with domain-specific data, hybrid human-AI systems, explainable AI

outputs, and ethical governance frameworks. With a review being situated at the intersection of Management Science and Accounting & Finance, it brings together theoretical approaches from decision sciences, organizational theory and financial regulation.

INTRODUCTION

Accounting and auditing is the job profession through which the most remarkable change in technology has taken place since the introduction of the computerized accounting system. AI is transforming the processing, analysis, and assurance of financial data using machine learning, natural language processing, robotic process automation, and generative large language models. The transition from sample-based inspection to complete population inspection and real-time decision making involves a paradigm shift rather than merely a change in speed. (Abdo-Salloum & Chehade, 2026).

The need for comprehending this transformation is growing, given the quick market uptake. Wolters Kluwer (2025) revealed in their report on AI in Tax & Accounting that the rate of adoption of AI among tax and accounting firms has quadrupled between 2024 and 2025, rising from 9% to 41%, with 35% of firms already using AI on a daily basis and 77% intending to invest more in AI over the next three years. This is due to the continued development of AI tools and client expectations that strategic business guidance is provided by embracing data-driven insights, with 35% of clients actively looking for such insights (Wolters Kluwer, 2025).

But there is significant uncertainty as well as optimism. According to AuditBoard's survey, while there's improvement in processing speed and data accuracy, fewer than 30% of accounting firms are ready to meet AI governance requirements. There is significant underutilization of AI in internal audit; only 7 percent have it in place at an advanced or high level, and only 28 percent of audit leaders are confident in their teams' ability to effectively audit AI risks (Jefferson Wells, 2025). The lack of

adoption and readiness is a serious threat for the profession.

This review aims to tackle the lack of synthesized information from the AI-accounting literature and to provide a comprehensive overview from an evidence-based perspective. What is the extent of the use of AI technologies in accounting and auditing, and what are they used for? (2) What are the types of AI technologies being used in accounting and auditing and what are they applied to? (2) What is the evidence (empirical) that exists on the effect of AI on efficiency, accuracy, and audit quality? (3) What are some of the barriers to adoption, and what are the differences in barriers across organizational contexts? (4) How to responsibly actualize the potential of AI in terms of research directions or policy interventions? The review sits at the intersection of Management Science and Accounting & Finance, and is based on systematic literature reviews, empirical studies and industry surveys, both theoretical synthesis and practical guidance.

2. Methodology

A systematic review approach modified from the PRISMA framework is used in this review. This literature corpus includes peer-reviewed journal articles, conference proceedings, and authoritative industry reports from the year 2020 to 2026.

The sources were located using Scopus, ScienceDirect, IEEE Xplore, the American Accounting Association journals, and publications of the major professional bodies. Both single terms, like "artificial intelligence," and compound terms, like "artificial intelligence and accounting," "accounting and auditing," "audit quality and accounting," "audit quality and natural language processing," "large language

models and accounting," "large language models and natural language processing," "natural language processing and accounting," "natural language processing and audit quality," "natural language processing and fraud detection," "natural language processing and robotic process automation," and "robotic process automation and fraud detection" were included in the search. Studies were included if they (1) related to the uses of AI in accounting, auditing, and/or related financial tasks; (2) included empirical evidence, systematic synthesis, or authoritative professional guidance; and (3) were published in English. The final corpus consists of 12 systematic literature reviews of 236 peer-reviewed papers published from 2014 to 2025 (Abdo-Salloum & Chehade, 2026), several large-scale surveys on accounting professionals and analyses of case studies about the implementation of the Big Four. The multi-source approach allows triangulation of findings and reduces the limitations of adopting a single methodological tradition.

3. AI Technologies Shaping Accounting and Auditing

3.1 Machine Learning and Deep Learning

The core AI technology in accounting and auditing is machine learning. For classification problems like transaction categorization, anomaly detection, financial distress prediction, supervised learning approaches like random forest, gradient boosting machine, support vector machine are used. To address the temporal dependency and correlations between fraud types in financial statements, deep learning algorithms, specifically long short term memory (LSTM) networks and hybrid LSTM-multilayer perceptron (LSTM-MLP) models, have shown promising results in detecting fraud. (Wang et al., 2025)

Studies such as the one by Wang, Chiu and Vasarhelyi (2025) have created a deep learning-based system for financial statement fraud prediction with remarkable prediction accuracy, along with the added value proposition of predicting the specific fraud. Research that combines the Fraud Triangle theory with

machine learning has also expanded the scope and feasibility of fraud detection in the context of emerging markets, specifically in the case of Vietnamese publicly listed companies, with 6,669 firm-year observations (Abdo-Salloum and Chehade, 2026).

Graph neural networks are a new frontier, especially in the audit of accounting journal entries. The method allows for risk-oriented, data-driven auditing by extracting relevant facts from large amounts of data and focusing audit resources on the most relevant areas. (Kassar & Jizi, 2026).

3.2 Natural Language Processing and Large Language Models

The development of natural language processing (NLP) has revolutionized the auditor's ability to handle textual material. A new era of possibilities has been brought about by the introduction of large language models (LLMs) such as GPT-4 and their domain-specific counterparts. In order to match accounting data, a new LLM-based continuous audit architecture collects audit information from text sources almost instantly. When used on a Brazilian government payroll system, this method might reduce cross-verification time by up to 83% when compared to paper-based approaches and increase extraction accuracy to 97.0%, enabling complete population testing as opposed to sampling. (Zhang et al., 2026).

AuditGPT, an LLM-based framework with retrieval-augmented generation (RAG), automatically checks financial auditing and regulatory compliance (Bohra et al., 2026). The challenge of applying deep learning natural language models to map natural language statements with European Union Accounting Directive codes is a task that has traditionally been costly for auditors (Kassar & Jizi, 2026). LLM analysis of audit documents provides automated hypertext assignment, generating context rich audit evidence that addresses the longstanding issue of evidence correlation in audits (Zhang et al., 2026).

The low accuracy and hallucination rates, however, limit LLM use in auditing. Models can produce accurate but incorrect results, which can be a serious problem in the high-stakes setting of audit, regulatory compliance and tax advice (Abdo-Salloum & Chehade, 2026). Domain-specific reasoning problems also limit the capacity to be consistent in interpreting complex accounting standards, or in applying subtle legal rules. (Jaworska, 2026).

3.3 Robotic Process Automation

AI components in RPA are applied widely to structured, rules-based tasks. Four areas of benefits are covered in the systematic analysis of AI and RPA benefits: financial, operational, quality reporting, and customer-related benefits (Kassar & Jizi, 2026). Automating expense vouching, filling out disclosure checklists, and extracting data from standard papers are all areas where RPA excels.

Intelligent automation is where you take RPA and you combine it with machine learning, so that is more than just following rules. Machine learning algorithms trained on an organization's historical data learn how the organization records its operations, and apply that pattern to new transactions, enabling adaptive automation that gets better over time. (Abdo-Salloum & Chehade, 2026).

3.4 Expert Systems and Hybrid Architectures

Expert systems, knowledge-based decision frameworks based on rules within a given domain, remain relevant in niche areas of auditing. Most importantly, hybrid architectures that combine multiple AI approaches, such as the RFECV-PRF feature selection method combined with GA-LightGBM optimization for financial fraud detection, represent the state of the art (Wang et al., 2025). These hybrid approaches exploit the complementary strengths of different algorithms to obtain detection accuracy and transparency that no single method can achieve provide.

4. Applications Across Accounting and Auditing Functions

4.1 Financial Reporting and Transaction Processing

Artificial intelligence can increase the credibility of financial reporting, including through automated data entry, intelligent classification of documents and detection of anomalies in accounting documents. Variational autoencoder (VAE) models are utilized for automatic categorization and anomaly detection in accounting records in order to overcome the low efficiency of conventional human procedures (Abdo-Salloum & Chehade, 2026). In computerized accounting systems, artificial intelligence improves decision-making, accuracy, and efficiency in data entry, fraud detection, auditing, and financial forecasting. (Siano et al., 2026).

4.2 Audit Planning and Risk Assessment

The empirical research supports the positive and significant relationship of the adoption of AI and the effectiveness of audit planning in terms of risk detection, efficiency and clarity (Abdo-Salloum & Chehade, 2026). AI helps auditors identify risks more accurately, become more efficient and focus on important work. EY Japan has created an AI agent (UTB Research) that automatically detects risk information in corporate disclosures, timely disclosure documents, and general economic reports that may result in financial statement misstatements, and documents the basis for each risk in a report. (EY Japan, 2025).

4.3 Fraud Detection

Financial statement fraud detection is one of the most researched AI applications. Traditional statistical techniques are consistently outperformed by deep learning models, graph-based techniques, and hybrid artificial intelligence systems. Hybrid AI techniques, particularly graph-based deep learning, provide creative ways to increase fraud detection accuracy and transparency, according to a thorough

literature evaluation of numerous indications (Wang et al., 2025). A emerging area of fraud detection is the use of LLMs to analyze temporal variations in the Management Discussion and Analysis (MD&A) parts of company filings. (Abdo-Salloum & Chehade, 2026).

4.4 Continuous Auditing and Real-Time Assurance

Continuous auditing, which provides textual assurance at or close to the moment of the events being certified, is significantly improved by AI. The LLM-assisted architecture for real-time cross-verification offers auditors without significant technical expertise a reproducible three-step process. It performs rule-based cross-verification, parses schemas, and aligns LLM capabilities with auditor-defined objectives (Zhang et al., 2026). As a result, the auditor's responsibilities change from conducting retrospective inspections to monitoring and making decisions in real time.

4.5 Management Accounting and Strategic Decision Support

There are three main ways that AI is changing management accounting. They are budgeting, cost analysis and performance measurement. AI allows for more accurate forecasting, real-time cost tracking, and prompt corrective actions in budgeting; transforms cost management from reactive to predictive and real-time in cost analysis; and improves the accuracy and efficiency of financial reporting in performance measurement (Abdo-Salloum & Chehade, 2026). Such developments are changing the role of management accountants from “number crunchers” to “strategic analysts” who interpret AI output for strategic recommendations (Siano et al., 2026). Agentic artificial intelligence systems: autonomous, contextually aware, goal-driven agents are an emerging frontier in management accounting, reshaping the boundaries of strategic decision-making (Wolters Kluwer, 2025).

5. Empirical Evidence of Impact

5.1 Efficiency and Productivity Gains

There are large efficiency gains in the empirical record. KPMG's Clara AI platform cut weekly auditor work hours by 18% with the lowest PCAOB deficiency rate (20%) of Big Four firms and no audit opinion errors in 2022–2023 (Siano et al., 2026). The cross-verification time was reduced by 83% with the LLM-aided continuous auditing framework (Zhang et al., 2026). A survey of 454 accounting professionals revealed improvements in processing speed and data accuracy. (AuditBoard, 2025).

5.2 Audit Quality

Adoption of AI is positively correlated with audit quality, according to empirical data. According to the study, there was a statistically significant positive correlation ($\beta = 0.347$) between the use of AI and audit quality in Nigerian audit businesses (Abdo-Salloum & Chehade, 2026). Internal audit quality in commercial banks was positively and significantly correlated with AI implementation ($\beta = 0.4$, $p < 0.01$), and augmented AI was more successful than purely autonomous systems ($\beta = 0.720$). (Kassar & Jizi, 2026). The study draws on a sample of 25,408 firm-year observations of Chinese firms and shows that standard development by clients results in decreasing audit lags and audit fees (Abdo-Salloum & Chehade, 2026). A quasi-natural experiment that exploited ChatGPT accessibility as an exogenous shock found that the absolute value of discretionary accruals, an inverse proxy for audit quality, decreased by about 8.99% for firms with subsidiaries in English-speaking countries after the launch of ChatGPT. (Li & Goel, 2026).

5.3 Fraud Detection Effectiveness

There is strong evidence that AI is better at detecting fraud. Compared with existing methods, deep learning-based financial statement fraud prediction systems have much higher prediction accuracy (Wang et al., 2025). Research confirms the positive impact of machine learning

and artificial intelligence in the efficacy of fraud detection and audits, demonstrating the novel promise of AI-enabled accounting information systems to impact organizational governance and control (Abdo-Salloum & Chehade, 2026). A survey study found that AI applications have a number of statistically significant positive effects on the accounting and auditing profession, mainly reflected in speed of task completion, improved quality and accuracy of outputs and enhanced ability to detect fraud. (Kassar & Jizi, 2026).

6. Challenges and Barriers to Adoption

6.1 Skill Gaps and Workforce Readiness

The biggest barrier to AI adoption is the scarcity of experts with the required technical expertise. The systematic review highlights the need for new digital competencies for auditors as a critical challenge (Abdo-Salloum & Chehade, 2026). 46% of leaders say that a lack of AI skills in the workforce is a top barrier, McKinsey finds (Jefferson Wells, 2025). Internal audit functions also cite lack of understanding or expertise as a barrier to implementation (61%) (AuditBoard, 2025). Only 28% of audit leaders are confident their teams have the skills to effectively audit AI risks (Jefferson Wells, 2025).

The skills gap isn't purely technical. "An investigation of Big 4 audit professionals revealed that the implementation of GenAI for auditing is impacted by elements like the profession's risk aversion, GenAI experience, perceived usefulness, ease of use, job insecurity, social influence, facilitating conditions, and technology awareness (Li & Goel, 2026). Junior and experienced auditors use GenAI differently, and audit experience and time constraints alter adoption patterns (Li & Goel, 2026).

6.2 Ethical and Regulatory Concerns

It's a big roadblock. Ethical issues. Critical research factors identified as ethical risks include skill gaps, deskilling, bias and data misuse that should be taken into account in practice and regulation (Abdo-Salloum & Chehade, 2026).

The quick deployment of AI-driven automated decision-making in accounting poses ethical risks around privacy, bias, and accountability (Jaworska, 2026). Other AI-specific risks include bias, overreliance on AI, data privacy violations, and the risk to auditor independence from delegating decisions to algorithms (Abdo-Salloum & Chehade, 2026).

From a legal point of view, the delegation of decision-making powers to artificial intelligence systems faces important limits, the lack of legal personality of artificial intelligence systems and their inability to apply critical expert judgment. AI tools vary a lot in their results and rely heavily on the assumptions, and the questions posed, and the auditor's interpretations (Jaworska, 2026). These tools should be employed solely as auxiliary support for accounting experts and not as standalone decision-making systems (Jaworska, 2026).

6.3 Data Quality and Technical Infrastructure

AI reliability is heavily dependent on data quality and availability. The quality and availability of data (Abdo-Salloum & Chehade, 2026) have a great impact on the concerns of auditors (33.33%) about the accuracy and reliability of AI results. Implementation challenges include data privacy, compatibility with existing systems, and barriers to adoption by small and medium-sized enterprises (Kassar & Jizi, 2026). High costs of investment in technological infrastructure are identified as a key challenge in systematic reviews (Kassar & Jizi, 2026).

6.4 Organizational and Psychological Factors

Adoption is determined by psychological and organizational factors. A systematic review identified perceived usefulness, ease of use and trust as influential factors in adoption (Abdo-Salloum & Chehade, 2026). According to the AuditBoard survey, following a robust initial adoption in May and June, acceptance rates for AI dropped by approximately 30% in July 2025, and decision-making times increased – indicating that early excitement may encounter a "middle

maturity trap” where inconsistent governance hampers the complete promise of AI (AuditBoard, 2025).

Job displacement concerns are still significant. Early studies indicate that accountants and auditors are not fully endorsing AI implementations, mainly due to concerns about job loss and trustworthiness of these technologies (Abdo-Salloum & Chehade, 2026). 42.86% of auditors surveyed in construction financial audits fear the replacement of human auditors.(Kassar & Jizi, 2026).

7. Future Directions and Research Agenda

7.1 Domain-Specific Model Development

The creation of domain-specific refined models is the top research priority. Relevance, precision, and reliability can also be significantly increased by fine-tuning LLMs on accounting-specific corpora including financial statements, audit reports, tax laws, and regulatory filings (Abdo-Salloum & Chehade, 2026). Improving auditability, interpretability, and regulatory compliance will require research on chain-of-thought prompting, retrieval-augmented generation (RAG), and citation-grounded generation (Zhang et al., 2026). Second, in order to objectively examine model capabilities, biases, and limits, comprehensive accounting-specific evaluation standards (such as AuditBench and PLAT) are required. (Li & Goel, 2026).

7.2 Hybrid Human-AI Systems

The evidence strongly supports a collaborative model rather than a substitutive model. Research that frames AI as a complement to human judgment emphasizes the need to formalize audit procedures and re-design workforce capabilities (Abdo-Salloum & Chehade, 2026). “Co-piloted” models that keep human expertise at their core will ensure that LLMs are an addition to, rather than replacement for, professional judgment, particularly in high-stakes areas such as auditing and taxation (Jaworska, 2026). This hybrid approach is empirically validated by the fact that Augmented AI is better than fully Autonomous

AI in terms of internal audit quality. (Kassar & Jizi, 2026).

7.3 Explainable and Verifiable Outputs

Regulatory acceptance and auditability are hampered by the opacity of many AI models, especially deep learning systems. Explainability strategies that make results drawn by AI transparent and verifiable must be given top priority in research. It is crucial to create reliable validation procedures and open deployment plans. (Zhang et al., 2026).

7.4 Frameworks for Ethical Governance

By developing best practices, disclosure standards, and accountability procedures for the use of AI, accounting research should proactively address ethical, privacy, and regulatory challenges (Abdo-Salloum & Chehade, 2026). To guaranty audit independence, data privacy and confidentiality, and accountability for AI-generated outputs, AI governance mechanisms must be established (Jaworska, 2026). The following are the seven prerequisites for the shift to an AI role: 1) Quality of data 2) The maturity of algorithms 3) Scalability of infrastructure 4) AI literacy within organizations; 5) frameworks for governance; 6) preparedness for regulations; and 7) feedback loops. A framework for assessing an organization's AI readiness is provided by these threshold conditions. (Siano et al., 2026).

7.5 Educational Reform

The findings of the systematic review emphasize the necessity for changes in accounting education that will prepare accounting professionals for working in environments that are driven by AI (Abdo-Salloum & Chehade, 2026). Ensuring that curricula are updated to incorporate data analytics, AI literacy, and skills for human-AI collaboration while maintaining the nurturing of professional skepticism, intellectual curiosity, critical thinking, and human-AI relationship-building abilities.

7.6 Longitudinal and Comparative Research

Hence, future studies should be longitudinal and mixed method approaches, and include practitioner-based studies to gain more empirical and practical insights (Abdo-Salloum & Chehade, 2026). Further research could focus on longitudinal analyses of adoption patterns, comparative analyses of the accuracy of AI systems in fraud detection, and more comprehensive examination of ethical considerations in establishing trust and confidence in AI systems. (Abdo-Salloum & Chehade, 2026).

8. Conclusion

AI is more than just a new accounting and auditing tool. It's a disrupter that is changing the landscaping of the professionals. The research evidence in this document demonstrates that AI has an impact on efficiency, accuracy, fraud detection, and audit quality. The use of AI in accounting has skyrocketed, as use by accounting firms has quadrupled in one year (Wolters Kluwer, 2025). However, this pace of acceleration is faster than the development of the governance systems, skills development programmes and regulations to ensure responsible deployment.

In conclusion, this review confirms that AI can be most beneficial as a decision support tool to complement, but not supplant, the human professional judgment. The most successful applications are those that are combined human-machine systems, where AI is used for tasks involving structured data and human workers bring in their skepticism, contextual understanding, and ethical judgment (Abdo-Salloum & Chehade, 2026; Jaworska, 2026). This model retains the core of professional judgment and still utilizes the advantages of computational capabilities from AI.

The take-home message for practitioners is that as crucial as investing in AI technology is the investment in AI training and governance infrastructure. The findings highlight the need for policy makers to create new regulations that are specific to the risks of AI and promote

innovation. The lesson to educators is that accounting education must keep up with the pace of AI and evolve to create an AI-empowered accounting cadre with the uniquely human skills that artificial intelligence cannot replicate. This new profession will be different, but fundamentally human, with an emphasis on judgment and accountability, analytical, strategic, and technology-enabled.

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