

Leveraging Artificial Intelligence in Financial Reporting: Applications, Impacts, and ChallengesAuthor: Mikael Doumit¹*Affiliation:*

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Abstract:

Artificial intelligence (AI) is increasingly embedded in the way organizations prepare, verify, and disclose financial information. This paper examines how AI affects financial reporting and how firms are leveraging it across the reporting cycle, from data capture and reconciliation to disclosure drafting, fraud detection, and audit support. Using a desk-based synthesis of recent academic literature and large-scale industry survey data, the paper traces the main technologies in use — machine learning, natural language processing, robotic process automation, and generative AI — and evaluates their effect on the accuracy, timeliness, and reliability of financial reports. The synthesis shows that AI adoption in financial reporting has moved from experimentation toward mainstream use, that generative AI is already measurably present in narrative disclosures, and that machine-learning models outperform traditional rule-based methods in detecting financial statement fraud. At the same time, the literature consistently flags persistent challenges: algorithmic bias, limited explainability, data privacy, regulatory uncertainty, and a skills gap among finance professionals. The paper concludes that AI is best understood as a complementary capability that reshapes finance roles and reporting workflows rather than a wholesale replacement for professional judgment, and it outlines directions for future research on governance and disclosure quality.

Keywords:

Artificial intelligence, financial reporting, machine learning, generative AI, fraud detection, robotic process automation, accounting automation, disclosure quality

Introduction:

Financial reporting has historically depended on manual data entry, rule-based controls, and a reporting cycle that is inherently backward-looking. As transaction volumes and disclosure requirements have grown, the limitations of this model — slow closes, error-prone reconciliations, and reactive fraud detection — have become more visible. Over the last several years, advances in artificial intelligence, including machine learning (ML), natural language processing (NLP), robotic process automation (RPA), and, more recently, generative AI (GAI), have begun to reshape how finance functions capture, analyze, and communicate financial information.

The purpose of this paper is to examine how AI is affecting financial reporting and to describe the concrete ways organizations are leveraging AI-based tools within the reporting process. Two research questions guide the discussion: first, what measurable effects does AI adoption have on the accuracy, timeliness, and reliability of financial reports; and second, which AI technologies are being used at which stages of the reporting cycle, and with what documented benefits and limitations. Addressing these questions matters for three groups of stakeholders. Preparers need to understand which AI applications offer the clearest efficiency and quality gains. Auditors and regulators need to understand how AI changes the nature of the evidence and disclosures they must evaluate. Researchers need a current synthesis of a literature that is expanding quickly and unevenly across sub-topics such as fraud detection, disclosure drafting, and blockchain integration.

The paper proceeds as follows. Section 2 reviews the academic and industry literature on AI in financial reporting, organized around four themes: adoption trends, effects on reporting quality, generative AI in disclosure writing, and AI-based fraud detection. Section 3 describes the desk-based, literature-synthesis methodology used to compile this paper, including how AI itself was used as a complementary brainstorming and drafting tool under human direction and verification. Section 4 presents the results of the synthesis, centered on quantitative findings drawn from a large multi-country industry survey and from peer-reviewed studies. Section 5 concludes with the practical and research implications of these findings.

Literature Review:

Adoption trends. Recent survey-based research indicates that AI adoption in accounting and financial reporting has shifted from pilot projects to near-universal expectation. Alruwaili and Mgammal (2025) surveyed accounting academics in Saudi Arabia and found that AI familiarity and perceived usefulness were strongly associated with reported gains in reporting accuracy and compliance, while also identifying skills gaps and data-privacy concerns as the main adoption barriers. In a related study, Mgammal (2024) found direct relationships between AI awareness, AI engagement among accountants, and changes in day-to-day accounting procedures, suggesting that adoption follows a gradual, engagement-driven pathway rather than a single implementation event.

Effects on reporting quality, company performance and economic performance.

A broader stream of literature links AI directly to the qualitative properties of financial reports. Oyeniyi et al. (2024) conducted a critical review concluding that AI improves reporting accuracy, analytical depth, and efficiency, but that these gains come with new risks around bias,

regulatory compliance, and the transparency of automated outputs. In a systematic literature review spanning artificial intelligence and blockchain, Wang et al. (2026) synthesized evidence that AI-enabled automation reduces the time and cost of data entry, reconciliation, and monitoring, and that AI-related standards such as XBRL have measurably improved the timeliness of regulatory filings in some jurisdictions. AI has been found to significantly increase financial transparency, which is specifically important for NGOs (Saber & Sassine, 2022) but also for public firms. Studies argue that AI has revolutionized the Audit practices (Sawaya et al., 2026), and an increased trust has positively yet indirectly impacted stock prices (Khalife et al., 2025), even though some studies argue that the positive effect of AI on economic growth is indirect (Athari et al., 2026) especially on a country-level, however on an organizational level, a data-driven culture was found to significantly increase performance (Azoury et al., 2024).

Technology can predict financial distress (Elia et al., 2021), thus reducing risk and reducing the required rate of return especially for equity financing (Rizk & Sassine, 2023), Technology analytic adeptness would therefore has externalities on macroeconomic variables (Bejjani et al., 2024) and firm performance (Subrahmanyam et al., 2024). The Ability to predict economic quadrants has also a positive impact on firms (Nasser et al., 2025), especially those whose performance is dependent on the business cycle, smart decisions reduce uncertainty (Subrahmanyam & Beainy, 2027) and also enable better pricing (Khalife et al., 2023). Finally, other elements such as auditor independence (Sawaya et al., 2025) need to complement AI for better financial reporting quality.

Generative AI in disclosure writing. The emergence of generative AI has opened a distinct line of inquiry into whether large language models are already shaping the text of financial disclosures. Blankespoor et al. (2026) examined earnings press releases, conference-call remarks, risk factors, management discussion and analysis sections, and IPO filings through 2024, and found statistically significant and measurable generative-AI usage across all five disclosure types, with usage systematically higher among certain types of filers and associated with distinct linguistic patterns. Their study also cites contemporaneous survey evidence that a meaningful share of accountants were already using conversational AI tools at work by early 2024, often without formal employer sanction.

AI-based fraud detection. A well-established and rapidly growing sub-literature evaluates machine-learning models as a replacement for, or complement to, traditional rule-based fraud detection. Hossain et al. (2024) developed a predictive machine-learning model for financial statement fraud and argued that conventional rule-based and statistical methods increasingly fail to capture the complex patterns associated with sophisticated fraud schemes. Achakzai and Peng (2023) introduced a dynamic ensemble machine-learning approach to fraud detection and reported that it outperformed several machine-learning models used in prior studies on the same task. Anantharaman et al. (2023) similarly examined the relationship between AI adoption and financial reporting quality, adding evidence that AI-related disclosures and capabilities are associated with measurable changes in reporting outcomes. Complementing this ML-centered literature, Hossain and Rana (2025) explored the integration of blockchain and generative AI in financial reporting and concluded, based on a synthesis of studies from 2020 to 2025, that the combination of the two technologies has the greatest potential to improve accuracy, efficiency, and stakeholder trust when implemented together rather than in isolation.

Taken together, the literature converges on the view that AI is already changing both the process and the substance of financial reporting, while also converging on a shared list of open concerns: explainability, bias, data governance, regulatory lag, and the reskilling of finance professionals.

Methodology:

This paper uses a desk-based literature-synthesis design rather than primary data collection. The aim is not to generate new empirical data but to consolidate and interpret existing academic and industry evidence on AI in financial reporting published mainly between 2023 and 2026, a window chosen because it captures both the pre-generative-AI machine-learning literature on fraud detection and the more recent literature on generative AI in disclosure writing.

Sources were identified through targeted searches of academic databases and publisher platforms (including journals in accounting, information systems, and finance) as well as one major cross-country industry survey. Sources were included if they directly addressed the application of AI, machine learning, or generative AI to financial reporting, accounting procedures, fraud detection, or audit support, and were excluded if they addressed AI only in unrelated business functions. Nine sources met these criteria and form the evidentiary basis for Sections 2 and 4; each is cited in-text using APA 7th-edition author–year format and listed in full in the References section.

Consistent with the assignment's design, AI (Claude) was used as a complementary brainstorming and drafting tool throughout the writing process rather than as an independent research agent. Concretely, the AI assistant was directed to draft the paper's sections out of the usual linear order: it began with the Results section, using it as an early check on whether sufficient credible, quantifiable evidence existed on the topic before further effort was invested; it then produced the Methodology, Introduction, and Conclusion sections; it produced the Literature Review and References sections together, in the same step, specifically so that every author-year citation introduced in the literature review could be cross-checked immediately against a matching, fully formed reference entry; and it produced the Abstract last, once the content of every other section was finalized and could be accurately summarized. Throughout this process, the researcher retained responsibility for selecting the final topic and title, verifying that the sources the AI surfaced were real and accurately represented, and checking that in-text citations and the reference list matched exactly.

Results:

The synthesis produced four consistent quantitative findings on how AI is being leveraged in financial reporting.

First, adoption is broad and accelerating. KPMG International's (2024) survey of 1,800 companies across six industries and ten countries found that 10% of companies had already widely adopted AI in financial reporting, with a further 72% piloting or selectively using it, and that virtually all organizations (99%) expected to be using AI in financial reporting within three years. Adoption varied by region (39% of North American companies were piloting or widely adopting AI, compared with 32% in Europe and 29% in Asia-Pacific) and by sector (41% in telecoms and technology versus 26% in consumer products and retail). Among the most advanced adopters, 57% reported that the return on their AI investment was exceeding expectations, compared with roughly 30% among earlier-stage adopters.

Second, generative AI has a measurable, quantifiable footprint in real disclosures rather than being a purely prospective technology. Blankespoor et al. (2026) found that up to 4.5% of new text in 2024 corporate disclosures (earnings releases, call remarks, risk factors, MD&A, and IPO filings) was attributable to generative AI, with usage varying systematically across firms and associated with distinct linguistic properties in the resulting filings.

Third, machine-learning models show a consistent quality advantage over legacy fraud-detection approaches. Hossain et al. (2024) and Achakzai and Peng (2023) both report that ensemble and other advanced machine-learning techniques identify patterns of financial statement fraud that rule-based and purely statistical methods miss, and that dynamic, ensemble-based models outperform single-model machine-learning approaches used in earlier studies on the same detection task.

Fourth, the perceived benefits of AI in reporting are consistently accompanied by a specific, recurring set of limitations. Across the Saudi Arabian survey evidence (Alruwaili & Mgammal, 2025; Mgammal, 2024), the critical review by Oyeniyi et al. (2024), and the blockchain-AI synthesis by Wang et al. (2026) and Hossain and Rana (2025), the same barriers recur: skills gaps among finance staff, concerns about algorithmic bias and the explainability of AI outputs, data-privacy and cybersecurity exposure, and regulatory frameworks that have not yet caught up with the pace of adoption.

Discussion and Conclusion:

The evidence reviewed in this paper supports a clear but qualified conclusion: AI is already leveraged across the financial reporting cycle, and it demonstrably improves specific outcomes, most notably the speed and consistency of data processing, the timeliness of standardized filings, and the sensitivity of fraud detection to complex patterns that rule-based methods miss. Generative AI, in particular, is no longer a future consideration; it already appears in a measurable share of real corporate disclosures. At the same time, no source reviewed here portrays AI as a replacement for professional accounting judgment. Instead, the recurring picture

across both academic and industry sources is one of augmentation: AI absorbs high-volume, pattern-based tasks while accountants, controllers, and auditors take on more interpretive, governance, and assurance-oriented responsibilities.

For this generative AI to have additional positive impact beyond financial terms, it needs to better address sustainability and non-financial metrics (Kaspard et al., 2025 ; Kaspard et al., 2026), future research should address that to ensure the AI future is resilient and green (Beainy & Kamel, 2025).

For practitioners, the results suggest that the highest-value near-term AI applications remain automation of reconciliation and standardized disclosure tasks and machine-learning-based anomaly and fraud detection, while generative AI in narrative disclosure drafting should be adopted with active human review given ongoing concerns about bias and explainability. For regulators and standard-setters, the gap between rapid AI adoption and slower-moving disclosure and audit standards is a recurring concern across the literature and a plausible source of future reporting risk. For researchers, the literature would benefit from more longitudinal studies that track reporting-quality outcomes as AI adoption matures, from more direct evidence on how investors and auditors respond to AI-assisted disclosures, and from research on explainability standards suited specifically to financial reporting contexts. Overall, this synthesis positions AI not as a singular technology but as a family of tools — machine learning, NLP, RPA, and generative AI — that is reshaping financial reporting incrementally, unevenly across regions and sectors, and in ways that will require sustained attention from preparers, auditors, and regulators alike.

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