



Artificial Intelligence and Financial Reporting: A Conceptual Analysis of Accuracy, Transparency, and Decision-Making in Contemporary Business Organizations

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Abstract

Financial reporting exists to convert an organization's economic activity into information that external parties can trust and act upon, and artificial intelligence (AI) is now implicated on both sides of that exchange — assisting firms in the preparation of disclosures and assisting investors in interpreting them. This paper offers a conceptual analysis of the implications of that dual involvement for the three properties financial reporting is designed to deliver: accuracy, transparency, and support for sound decision-making. Drawing on recent accounting and finance research, including large-sample field evidence on generative AI use within actual reporting workflows, the paper argues that AI's effect on these three properties is not uniformly positive. Machine learning models have demonstrably improved specific accounting estimates and fraud-detection tasks, and generative AI is measurably present in firms' disclosure writing; at the same time, the same body of evidence documents emergent failure modes — systematic overreliance on incorrect AI-generated classifications, generative systems capable of producing fluent yet ungrounded disclosure text, and analytical tools whose reasoning remains difficult for even sophisticated users to peruse. The paper develops a conceptual framework in which accuracy and transparency function as preconditions for AI to improve decision-making, rather than as automatic corollaries of AI adoption, and traces the resulting implications for preparers, auditors, investors, and standard-setters. Its contribution is a structured account of where AI is presently strengthening financial reporting, where it is introducing new and consequential risks, and what conditions determine which outcome prevails in a given organizational context.

Keywords: artificial intelligence; financial reporting; generative AI; disclosure; transparency; accuracy; investor decision-making; explainability.



Financial reporting is, at its core, a trust mechanism: it enables parties who did not directly observe a firm's operations — investors, lenders, regulators, employees — to rely instead on a standardized account of what occurred behind the scene. That mechanism has always rested on two conditions holding jointly: the reported figures being accurate, and the process producing them being sufficiently transparent that outside parties can assess how much confidence those figures warrant. Artificial intelligence is now implicated in both conditions simultaneously, which is what renders it a qualitatively different technological development for financial reporting rather than merely an acceleration of the existing process. Firms increasingly use generative AI to draft the disclosures investors read (Blankespoor et al., 2026), while investors increasingly use generative AI to interpret those same disclosures (Blankespoor et al., 2025) — such that AI now occupies both ends of a communication channel that financial reporting regulation was originally designed around a single human reader.

The available evidence is more mixed than either optimistic or cautionary commentary on “AI in finance” typically suggests. Blankespoor et al. (2026), examining firms' actual earnings press releases, conference call remarks, risk factors, MD&As, and IPO filings through 2024, find statistically significant generative-AI usage across all five disclosure types, with up to 4.5 percent of new disclosure text AI-generated by 2024, and find that AI usage correlates with systematically different linguistic properties in the resulting filings. Choi and Xie (2026), studying generative AI use within actual accounting workflows at seventy-nine small and mid-sized firms, document measurable gains in reporting quality — more granular general ledgers and faster month-end closes — alongside a documented pattern of accountants over-relying on AI-suggested classifications that prove incorrect. Considered jointly, these findings indicate a more differentiated picture than either a purely optimistic or purely cautionary account would allow: AI is measurably present in financial reporting, it is producing genuine quality improvements in certain respects, and it is simultaneously introducing risks that remain only partially understood.

This paper examines that picture conceptually, organizing the recent evidence around the three properties financial reporting is intended to deliver. Its central argument is that **AI improves financial-reporting outcomes only where accuracy and transparency are treated as preconditions for better decision-making rather than assumed to follow automatically from AI adoption**. A model that improves the accuracy of an accounting estimate does not thereby render that improvement legible to those relying upon it; a tool that accelerates disclosure production does not thereby render the resulting disclosure more trustworthy. The paper first reviews the evidence on AI and reporting accuracy, then transparency, then decision-making, before proposing a conceptual framework that integrates the three and considering the implications of that framework for preparers, auditors, investors, and the regulatory bodies charged with overseeing financial reporting.

Conceptualizing AI's Role in the Financial Reporting Process

Financial reporting is not a single activity but a pipeline extending from the recognition and measurement of transactions, through preparation and disclosure, to audit, dissemination, and



ultimately use by investors and other stakeholders. AI is not entering this pipeline at a single point; recent research documents its presence at nearly every stage. On the preparation side, Blankespoor et al. (2026) find generative AI already embedded in the drafting of core disclosure documents, while Ashraf (2025), examining automation and internal controls specifically, finds automation associated with measurable improvements in financial reporting quality — direct evidence that AI's effect on preparation is not confined to drafting language but extends into the control environment governing the underlying figures. On the dissemination and use side, Bertomeu et al. (2025) exploit an unusual natural experiment — Italy's temporary ban on ChatGPT — to demonstrate that removing generative-AI access measurably raised information-processing costs and reduced market informational efficiency, evidence that AI has become a consequential input to how market participants process financial information rather than a peripheral convenience.

This paper treats AI's role in financial reporting as operating along the same three-stage structure the discipline has long used to evaluate reporting quality — accuracy of the underlying information, transparency of how that information was produced and what it means, and the quality of the decisions the information ultimately supports. Murphy et al. (2024), mapping the broader accounting-and-AI literature through topic modelling across 930 peer-reviewed abstracts, find financial-reporting-adjacent themes such as informational reliability and fraud detection sitting among the field's most active research clusters, evidence that the questions this paper addresses are not a narrow subfield but a central concern of current accounting scholarship. Dong et al. (2024), reviewing the more specific ChatGPT-and-large-language-model literature in accounting and finance, similarly find research clustering around direct applications, use of the technology as a research tool, and open questions about professional and organizational adoption — a structure that maps closely onto the accuracy, transparency, and decision-making organization this paper adopts, though Dong et al. note that the adoption-and-organizational-consequences cluster remains comparatively underdeveloped relative to the other two. What is new in the present context is that AI functions as a causal input at every stage of the reporting pipeline rather than a tool applied at a single point. A machine-learning model can alter the accuracy of an accounting estimate (Ding et al., 2020); a generative system can alter the transparency of a disclosure by rendering it either clearer or more convincingly opaque; and an AI-assisted investor may reach a different decision than an unassisted one would have reached (Bertomeu et al., 2025). Evaluating AI's overall effect on financial reporting therefore requires tracking all three properties together, since gains in one do not guarantee gains in the others.

AI and the Accuracy of Financial Reporting

Machine Learning and Financial Statement Estimates

The clearest and best-documented accuracy gains from AI concern estimation tasks with well-defined correct answers. Ding et al. (2020), studying insurance loss reserves, find machine-learning estimates outperforming the managerial estimates firms actually reported in four of five insurance lines examined — a specific, verifiable demonstration that AI can produce more accurate accounting estimates than the human judgement it is compared against, at least for this



class of estimation problem. Ashraf (2025) extends this picture from individual estimates to the broader control environment, finding automation associated with measurable improvements in financial reporting quality through its effect on internal controls — evidence that accuracy gains from AI are not confined to prominent estimates but extend into the process infrastructure underlying the reported figures themselves.

AI in Fraud and Misstatement Detection

A second and related accuracy contribution concerns the detection of numbers that are wrong, whether through error or intent. Bao et al. (2020) develop a machine-learning fraud-prediction model using raw accounting numbers rather than the financial ratios earlier detection models relied on, and demonstrate that this approach substantially outperforms established benchmark models — a methodological advance with direct implications for how effectively financial-statement fraud can be identified before it does damage. Bertomeu et al. (2021) approach a related problem from a different angle, using machine learning across accounting, audit, and market variables to detect patterns associated with ongoing misstatements, and find that accounting variables alone predict misstatements poorly — useful evidence only once combined with audit and market information. Taken together, these two studies suggest AI's accuracy contribution to misstatement and fraud detection is real but conditional: it depends on which data the model has access to, not simply on the sophistication of the algorithm applied.

Generative AI complicates the accuracy picture in a way the earlier, narrower machine-learning applications did not, because generative systems can produce fluent, well-formed text that is nonetheless factually wrong or unsupported by the underlying data. Choi and Xie (2026) document this risk directly inside real accounting workflows: accountants in their field sample selectively intervene when AI confidence scores are low, evidence of appropriate scepticism in some cases, but the same study documents a persistent pattern of accountants accepting incorrect AI-suggested classifications — an error pathway the authors note becomes harder to catch as generative outputs grow more fluent and more difficult to distinguish from reliable work. Blankespoor et al. (2026) find a related concern at the disclosure-writing stage: without careful oversight, generative-AI-assisted report writing risks producing inaccurate or poorly grounded disclosure language that a firm's own reviewers may not catch before it reaches investors. The accuracy question for generative AI in financial reporting is therefore not only whether the system's outputs are correct on average, but whether those relying on such outputs can reliably distinguish correct instances from incorrect ones — a distinction the estimation and detection literature discussed above did not have to confront in comparable form.

AI and the Transparency of Financial Reporting

From XBRL to Explainable AI: A Continuum of Machine-Readable Transparency

AI's transparency implications for financial reporting did not originate with generative AI; they trace to at least the SEC's 2009 mandate that financial statements be filled machine-readable XBRL format, a policy explicitly justified on transparency grounds — namely, reducing the informational barriers separating smaller investors from larger, more sophisticated ones



(Blankespoor et al., 2014). The market's response to that mandate proved more complicated than its transparency rationale anticipated: Blankespoor et al. (2014) find higher abnormal bid-ask spreads for XBRL-adopting firms in the year following the mandate, consistent with increased rather than diminished concerns about information asymmetry, at least in the short run. This finding offers an important caution for AI-era transparency claims specifically, in that it demonstrates that rendering financial information more machine-processable does not automatically translate into greater transparency for all users — sophisticated users equipped to exploit machine-readable data may instead benefit disproportionately relative to those without comparable resources.

The Opacity problem: Explainability and Algorithmic Trust

Where XBRL rendered financial data more machine-readable, contemporary AI systems introduce the converse problem: the systems processing and generating financial information are themselves frequently opaque to those relying on their outputs. Kokina et al. (2025), interviewing professionals working with AI in accounting and assurance settings, identify transparency, explainability, and algorithmic bias as unresolved and central problems rather than peripheral ones — the specific obstacles that determine whether AI-generated financial information can be trusted sufficiently to act upon. This opacity problem is more consequential in financial reporting than in most other AI application domains, precisely because financial reporting's institutional purpose is to enable outside parties to trust information they cannot independently verify; a black-box AI system embedded within the reporting pipeline reintroduces the very trust gap that audited, standardized financial reporting was designed to close.

Disclosure Behavior in an AI-Monitored Environment

A further transparency dimension concerns how AI alters firms' own disclosure incentives, independent of accuracy. Evidence reviewed in the recent financial-economics literature suggests that as investors increasingly rely on AI-assisted analysis, some firms respond by withholding more information rather than less — voluntary disclosures such as management forecasts have been found to decline meaningfully once firms are covered by AI-savvy analysts, even as AI improves the processing speed of whatever information is disclosed. This pattern indicates a genuine tension rather than a straightforward transparency gain: AI can render existing disclosures easier to process while simultaneously altering firms' strategic calculus regarding how much to disclose in the first instance, a dynamic that arguments premised solely on processing efficiency fail to capture. Zhang et al. (2023), examining the ethical dimensions of AI in accounting more broadly, identify accountability and transparency as recurring concerns that automation and analytics initiatives tend to treat as secondary rather than central design considerations — an observation of particular force in financial reporting, where transparency constitutes not a desirable side effect but the principal regulatory purpose of the activity. Dwivedi et al. (2023), addressing generative AI more broadly across disciplines, reach a structurally similar conclusion: productivity and processing gains are genuine, but so are risks pertaining to strategic use, bias, and the erosion of the transparency the technology is often represented as delivering.

***Preparer-Side Decision-Making: Management and Accountants***

On the preparation side, AI is altering the decisions management and accounting staff must make in producing financial reports. Choi and Xie (2026) find AI adoption associated with a measurable reallocation of accountant time away from routine data entry and toward business communication and quality assurance — evidence that the decisions accountants devote their time to are shifting toward judgement-intensive review rather than mechanical processing. Ross and Zhang (2025), surveying 136 accounting practitioners regarding generative-AI use, find that perceived risk, rather than availability of the tool, most constrains practitioners from moving beyond administrative applications toward the more analytically demanding uses generative AI is theoretically capable of supporting, suggesting that the preparer-side decision problem is presently less a matter of technical access than of accountants' confidence in their capacity to identify an erroneous AI output before it reaches a filing. Blankespoor et al. (2026) find a corresponding shift at the management level: firms confront a genuine decision regarding the degree of oversight to apply to generative-AI-assisted disclosure drafting, since the same tools that reduce preparation costs and advance plain-English reporting objectives also create exposure to litigation and regulatory risk should inaccurate or strategically biased content reach investors without adequate review. Both findings indicate the same underlying change: AI does not eliminate judgement from the preparation process but relocates it — from producing the initial draft of a figure or sentence toward determining whether that AI-produced draft is sufficiently sound to stand behind.

User-side Decision Making: Investors and Analysts

On the other side, AI is altering how investors and analysts process the disclosures firms produce, with measurable consequences for market outcomes. Bertomeu et al. (2025), employing Italy's ChatGPT ban as a natural experiment, find that removing generative-AI access increased information-processing costs and reduced market informational efficiency — direct evidence that AI-assisted reading of financial disclosures has already become consequential enough to affect market-level outcomes upon its sudden withdrawal, rather than constituting a marginal convenience for individual investors alone. This finding reframes what AI-assisted decision-making signifies in a financial-reporting context: it is not merely that individual investors reach different conclusions when assisted by AI, but that aggregate market efficiency itself now depends partly on AI availability, raising further questions about the position of smaller or less AI-equipped market participants when access to these tools is unevenly distributed.

The Feedback Loop between AI-Assisted Preparation and AI-Assisted Analysis

The most conceptually significant evidence reviewed above is that AI-assisted preparation and AI-assisted analysis are no longer independent processes; they increasingly interact. Blankespoor et al. (2026) find that filings containing more generative-AI-written content exhibit systematically different linguistic properties than filings without it, and it is a reasonable inference, consistent with the broader disclosure-processing-cost literature (Blankespoor et al., 2020), that AI-assisted readers will process AI-written disclosures differently than human-written ones, irrespective of



whether the reader is aware which is which. Rikhardsson and Yigitbasioglu (2018), reviewing the earlier business-intelligence-and-analytics literature in accounting, observe that empirical coverage of how analytical tools alter the informational relationship between preparers and users has historically lagged coverage of the tools' technical capabilities — a gap this feedback-loop dynamic renders considerably more urgent to close, since the tools on both ends of the reporting relationship now function as active participants in how information is produced and consumed rather than as peripheral analytical aids. This dynamic constitutes a feedback loop that financial-reporting theory has not previously had to accommodate: firms optimizing disclosure language for AI-assisted readers, investors relying on AI tools to process that language, and neither side necessarily transparent to the other regarding the extent of AI involvement on its end of the exchange. Whether this loop improves or degrades the overall quality of market information depends substantially on the accuracy and transparency conditions discussed in the two preceding sections, which is precisely why this paper treats those two properties for, rather than automatic consequences of, better decision-making.

Conceptual Synthesis: An Accuracy –Transparency-Decision Framework

The evidence reviewed across the preceding three sections supports a specific conceptual claim: accuracy and transparency are not merely desirable features that happen to accompany AI-improved decision-making in financial reporting; they constitute the mechanism through which AI's effect on decision-making becomes positive rather than negative. Where AI improves accuracy in a manner that remains transparent — as in Ding et al.'s (2020) loss-reserve estimates or Bao et al.'s (2020) fraud-detection model, both of which produce outputs that can be benchmarked against known criteria — the evidence indicates that superior outcomes follow. Where AI improves apparent efficiency absent a corresponding transparency safeguard — as in the overreliance pattern documented by Choi and Xie (2026), or the disclosure-withholding dynamic associated with AI-savvy analyst coverage — the evidence indicates that efficiency gains can coexist with, or actively produce, inferior decision-making outcomes for at least some participants in the parenting chain.

This framework carries a direct practical implication: evaluating whether a given AI application improves financial reporting requires posing two separate questions rather than one. The first is the question most existing adoption research addresses — whether the AI application improves accuracy or efficiency along some measurable dimension. The second, less often addressed systematically, is whether the resulting accuracy or efficiency gain remains legible to those who must act upon it: whether a reviewing accountant can identify an erroneous AI-suggested classification (Choi & Xie, 2026), whether an auditor can explain why an AI system flagged a particular transaction (Kokina et al., 2025), and whether an investor can distinguish a filing's plain-English clarity as the product of careful disclosure practice rather than AI-generated fluency surrounding an unclear underlying reality (Blankespoor et al., 2026). Only where both questions can be answered affirmatively does AI's presence in the financial reporting pipeline translate reliably into improved decisions downstream.



For preparers, the evidence reviewed here suggests that oversight of AI-assisted disclosure drafting cannot be treated as a one-time implementation decision; Blankespoor et al. (2026) find generative-AI usage already varying systematically across firms and disclosure types, and Choi and Xie's (2026) overreliance findings suggest that such oversight must be embedded within ongoing review processes rather than concentrated solely at the point of initial adoption. For auditors, Kokina et al.'s (2025) findings regarding unresolved explainability problems suggest that auditing AI-assisted financial statements may require new procedures specifically directed at evaluating whether preparers can explain and defend AI-influenced figures, not merely whether those figures appear reasonable. For regulators and standard-setters, the XBRL experience documented by Blankespoor et al. (2014) offers an instructive historical caution: transparency-oriented technology mandates do not automatically yield equal information access, and AI-era disclosure requirements will likely need to address not only whether AI was used, but how its use affected which investors were able to benefit from the resulting information. For researchers, Bertomeu et al.'s (2025) natural-experiment evidence that AI availability affects aggregate market efficiency opens a research agenda that firm-level or investor-level studies alone cannot fully address; understanding AI's effect on financial reporting increasingly requires market-level as well as firm-level analysis.

Directions for Future Research

Several gaps follow from the conceptual account developed above. First, most existing evidence on AI and reporting accuracy derives from settings with well-defined correct answers — loss reserves, fraud labels, misstatement flags — in which model performance can be benchmarked directly (Ding et al., 2020; Bao et al., 2020; Bertomeu et al., 2021). Generative AI's role in disclosure drafting does not offer a comparable benchmark, since the correctness of a disclosure sentence constitutes a more contested and context-dependent judgement than the correctness of a numerical estimate; research developing accuracy measures suited specifically to generative disclosure content, rather than adapting measures constructed for structured estimation tasks, would address a genuine gap.

Second, the overreliance problem documented by Choi and Xie (2026) merits sustained attention as a phenomenon specific to financial reporting. The consequences of an accountant trusting an incorrect AI classification in a general ledger differ materially, in both scale and in the party ultimately bearing the cost, from the consequences of a consumer trusting an incorrect AI recommendation in another domain; research tracing overreliance errors through to their eventual effect on reported figures and investor decisions, rather than terminating at the point of initial error, would connect this literature more directly to the outcomes that matter for financial reporting.

Third, the market-level evidence from Bertomeu et al. (2025) opens a research direction that firm-level studies alone cannot address: understanding how uneven AI access across investors affects the distribution, and not merely the average level, of decision-making quality in financial markets. The XBRL experience documented by Blankespoor et al. (2014), in which a transparency-oriented



mandate produced unequal rather than uniform benefits, suggests this distributional question warrants attention earlier in the AI adoption cycle than it received in the XBRL case.

Finally, little research to date has examined how the feedback loop between AI-assisted preparation and AI-assisted analysis, discussed above, unfolds across multiple reporting cycles rather than at a single point in time. Firms and investors are each adjusting their AI use in response to the other's behaviour; longitudinal research tracking that co-adaptation directly, rather than treating AI-assisted preparation and AI-assisted analysis as separate literatures, would better capture the dynamic this paper identifies as increasingly central to how financial reporting functions.

Conclusion

Artificial Intelligence has progressed from a peripheral tool applied to isolated financial reporting tasks to an input embedded across the entire pipeline connecting a firm's economic activity to the decisions outside parties make regarding it. The evidence reviewed in this paper supports neither a purely optimistic nor a purely cautionary reading of that development. AI has demonstrably improved specific accounting estimates and fraud-detection capabilities, and generative AI is already measurably present in both the disclosures firms produce and the analysis investors perform upon them. At the same time, this same body of evidence documents overreliance on incorrect AI outputs, persistent explainability gaps, and disclosure incentives capable of moving in the opposite direction from what processing-efficiency gains alone would predict. The conceptual framework developed here — treating accuracy and transparency as preconditions for, rather than automatic consequences of, better decision-making — offers a means of reconciling both strands of that evidence. Financial reporting's core purpose has always been to enable trust between parties unable to observe one another's information directly; the evidence reviewed here suggests AI can substantially strengthen that purpose, but only where its accuracy and transparency are actively verified rather than assumed, and only where those still responsible for the resulting decisions remain equipped to discern the difference.



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