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Review Article

How Reliable are AI-Generated Financial Disclosures Compared to Human-Written Disclosures, and what Audit Procedures are Necessary to Ensure their Accuracy and Integrity?

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Abstract

Graphical Abstract:

The quick use of generative artificial intelligence (GenAI), especially large language models (LLMs), is changing the way companies report and share financial information. GenAI is becoming more and more popular with finance teams for writing the narrative parts of annual reports, management discussion and analysis (MD&A), sustainability disclosures, and earnings releases. This is because it promises big gains in efficiency and more consistent messaging. At the same time, regulators, standard setters, and audit firms warn about new risks to reliability, including hallucinations, bias, loss of explainability, and weak controls over AI workflows. This paper offers a conceptual and normative examination of (1) the reliability of AI-generated financial disclosures in comparison to human-written disclosures, and (2) the requisite audit procedures and governance mechanisms necessary to guarantee accuracy and integrity. We synthesize evidence on the impact of AI on the quality of financial reporting and audit by using recent empirical and conceptual literature in auditing and accounting information systems, as well as practitioner reports and regulatory guidance. Research in banking and external auditing indicates that the utilization of AI is positively correlated with the quality of financial reporting and external audits, facilitated by enhanced information processing. Simultaneously, survey data reveals apprehensions regarding ethical dilemmas, requisite professional diligence, and professional discernment in the extensive application of AI within the auditing process. We suggest a conceptual framework for evaluating the dependability of AI-generated disclosures that encompasses: (a) the design of AI systems and training data; (b) internal control over financial reporting

(ICFR) and AI-specific controls; (c) governance and oversight by management, audit committees, and regulators; and (d) independent verification by external auditors. Building on existing auditing standards (for example, ISA 315 and ISA 330) and emerging technology guidance, we outline a set of risk-based audit procedures tailored to AI-generated narrative disclosures, including data lineage testing, model governance evaluation, analytical procedures on AI text, and expanded documentation requirements. The paper concludes that AI-generated financial disclosures can be at least as reliable as human-written disclosures - and in some dimensions more reliable - provided that entities implement strong AI governance, maintain human-in-the-loop review, and that auditors adapt their methodologies to explicitly address AI-related risks. In the absence of such controls and audit responses, GenAI can materially undermine the reliability, auditability, and credibility of financial reporting.

Keywords: Generative AI (LLMs), AI-generated financial disclosures, AI governance & ICFR SEC, Risk-based auditing (ISA 315/ISA 330).

1. INTRODUCTION

Generative AI and large language models (LLMs) such as GPT-class systems are rapidly being embedded into financial reporting and disclosure processes [1]. Corporate reporting platforms now offer GenAI functionality to draft narrative sections of annual reports, sustainability reports, and regulatory filings based on structured data and prior disclosures [2,3,16]. Finance leaders view these tools as a way to manage increasing reporting complexity, including new environmental, social, and governance (ESG) requirements, without proportionally increasing staff [2,3].

Regulators also stress that management is still responsible for the accuracy and completeness of financial disclosures, no matter if they are made by people or AI. The Public Company Accounting Oversight Board (PCAOB) and the Center for Audit Quality (CAQ) talk about the pros and cons of using AI in audits and financial reporting. They stress that AI needs to work within strong governance, control, and audit frameworks [4,5,7]. The International Auditing and Assurance Standards Board (IAASB) and other international bodies, as well as external auditors and national standard setters, have also started to give advice on technology and AI [6,12–14].

In light of this, two important questions come to mind: (1) How does the reliability of AI-generated financial disclosures stack up against human-written disclosures? and (2) What audit procedures and governance mechanisms are needed to make sure they are correct and honest? Academic literature directly comparing AI-generated versus human-written corporate disclosures is still limited, but adjacent work in financial economics, credit risk modelling, and auditing provides useful evidence about how GenAI affects text quality, information processing, and control environments [1,8,10,17,18]. Regulatory and professional publications complement this with early guidance on risk management and assurance [4–7].

This paper synthesizes these emerging strands of evidence and proposes a conceptual framework and audit response for AI-generated financial disclosures. It is designed as a conceptual review for practitioners, regulators, and academics, and does not present new empirical data. Instead, it integrates existing work to propose a structured way to evaluate reliability and determine appropriate audit procedures.

2. Background: Financial Disclosures, Generative AI, and Auditing

2.1 The role of narrative financial disclosure

Financial disclosures include both structured numerical data and extensive narrative components, such as MD&A, risk factors, business overviews, and ESG discussions. Narrative disclosure plays a key role in communicating strategy, risks, performance, and forward-looking information. Prior research shows that textual features such as readability, tone, and specificity are associated with earnings persistence, market reactions, and cost of capital [17,18].

Traditional narrative disclosures are drafted by management with input from legal counsel and investor relations. This process is time-consuming and subject to fatigue, strategic obfuscation, and stylistic inconsistency. Yet it is also grounded in tacit knowledge of the business and professional judgment that can be difficult for AI to replicate.

2.2 Generative AI and corporate reporting

Recent advances in GenAI enable systems that draft long-form, coherent, and financially sophisticated text based on structured and unstructured data. Corporate performance management and disclosure management vendors market GenAI features that can draft narrative explanations from financial data trends, suggest improvements to existing text, and generate alternative phrasings aligned with regulatory and peer norms [2,3,16]. They can also summarize or transform disclosures for different channels, such as press releases and investor presentations.

Wolters Kluwer, for instance, talks about GenAI-enabled tools that make draft narratives and find problems, while also stressing the need for human review and explainable AI [2]. Finrep's disclosure management platform also has generative tools for writing and comparing disclosures, but it stresses the need for statements that are backed up by evidence and clear discussions of AI's limitations and risks [3].

Simultaneously, studies in financial economics illustrate GenAI's capacity to analyze extensive financial texts, recognize comparable firms, condense disclosures, and enhance forecasts of economic results [8,17,18]. This means that GenAI can have a big impact on how people who prepare and use financial reports deal with narrative information.

2.3 AI in auditing and financial reporting: Current state

For over ten years, the auditing profession has been trying out AI and automated tools, starting with machine learning and robotic process automation. More recently, applications have grown to include risk assessment, document review, full-population testing, and anomaly detection [9,10,11,19]. A literature review conducted by Almufadda and Almezeini underscores the extensive applications of AI in auditing and observes that major audit firms have made substantial investments in AI platforms for journal entry testing, contract review, and risk assessment [10].

Empirical work in Jordanian banks shows that AI use is positively associated with external audit quality, with financial reporting quality mediating this relationship [1]. Survey evidence from an emerging market indicates that external auditors expect AI to enhance audit effectiveness but worry about its impacts on due professional care, competence, judgment, and ethical challenges [9,11]. KPMG's global survey reports that only a minority of firms have widely adopted AI in financial reporting, but most are piloting or using it selectively, with rapid growth expected [16].

3. Reliability of AI-Generated Versus Human-Written Disclosures

3.1 Defining reliability in the context of financial disclosure

For financial reporting purposes, reliability of disclosures can be understood along several dimensions: (a) accuracy, or factual correctness and alignment with underlying financial data; (b) completeness, or coverage of all material information required by the reporting framework; (c) neutrality and balance; (d) consistency in policies and terminology across periods; and (e) verifiability and auditability, meaning that statements can be traced back to evidence [6,12–14]. These dimensions map to common financial reporting quality constructs and to audit assertions under standards such as ISA 315 and ISA 330 (for example, completeness, accuracy, occurrence, and presentation).

3.2 Potential advantages of AI-generated disclosures

Several potential advantages of AI-generated narrative disclosures emerge from practice and empirical work:

- Quickness and ability to grow. GenAI can write long drafts of stories in just a few seconds, which cuts down on the time needed to prepare and takes the pressure off of reporting teams [2,3,16].
- Consistency within the system and alignment of data. When LLMs are combined with structured data, they can be limited to creating text directly from the underlying numbers and metadata. This can help reduce mistakes and inconsistencies in manual transcription. Vendors say that AI can find strange patterns and anomalies before they show up in final disclosures [2].
- Better readability and consistency. Empirical research on GenAI-refined texts in credit decision-making indicates that AI-refined texts differ from human-authored ones in terms of length, semantics, and linguistic characteristics, and can enhance predictive accuracy while maintaining interpretability [8]. Standardized templates and styles in financial disclosures may make it easier to compare and read them.
- More in-depth analysis. LLMs can cross-reference large datasets, previous disclosures, and external sources, which could lead to more detailed explanations than humans who are short on time can give. Studies on financial statement analysis using LLMs indicate that these models can extract and integrate value-relevant information, occasionally matching or surpassing traditional models in predictive tasks [18].

3.3 Risks and limitations of disclosures made by AI

Even though AI-generated disclosures have these benefits, they also come with big risks:

- Hallucinations and lies. When prompts are vague or data sources are missing, LLMs can make statements that sound true but are not. Regulators and practitioners stress that hallucinations, bad data provenance, and not being able to explain things are important failure modes to keep an eye on [3–5,7].
- Managing tone and bias. GenAI can unintentionally learn and spread biased or overly positive story patterns that are already in the training data or prompts. If models depend significantly on historical disclosures, they may incorporate prevailing disclosure biases and neglect to assimilate new information [17].
- Loss of professional judgment and context. Narrative disclosures frequently necessitate discerning judgment regarding materiality, prospective risks, and strategic positioning. GenAI should be an assistant, not a replacement, according to practitioner guidance. Humans must edit, put AI drafts in context, and check their accuracy [2,5,11].
- Problems with audit trails and explainability. When AI outputs don't have clear logs and data lineage, it can be hard for auditors to figure out how statements were made. Oversight bodies stress the importance of having full audit trails,

versioning, and records of the inputs and outputs of models [3,4,6].

Keeping data safe and private. When you use outside AI services with private, sensitive financial data, it can be hard to keep that data private and follow the rules. Guidance stresses how important it is to have access controls, keep data separate, and make sure that proprietary data isn't used to train general models [2–4,16].

3.4 Proof of AI, the quality of financial reporting, and the quality of audits

Direct empirical comparisons between AI-generated and human-written corporate disclosures are just starting to emerge. However, pertinent studies elucidate the implications of reliability.

First, data from Jordanian banks show that using AI is positively and significantly linked to the quality of external audits, with the quality of financial reporting acting as a mediating variable [1]. Second, research comparing loan officers' evaluations with GenAI-refined texts indicates that models incorporating AI-refined texts alongside structured data produce superior default prediction and business profitability compared to those utilizing solely human-written texts, implying increased informativeness of narrative content [8]. Third, research on financial statement analysis using LLMs shows that these models can systematically look at statements and find information that is important to value [18].

Surveys and conceptual papers on auditing stress that AI can enhance coverage and analytical skills, but it also brings up new ethical and governance issues, especially when it comes to professional judgment and accountability [9–11,19]. Current evidence indicates that AI, when properly regulated and supplemented by human oversight, can enhance certain aspects of reliability; however, in the absence of robust controls, hallucinations, bias, and opacity may compromise reliability. As shown in Table 1, AI-generated disclosures tend to perform better on consistency, while human-written disclosures currently have advantages in auditability.

3.5 Illustrative scenarios of AI-generated disclosures in practice

To further clarify the reliability implications, it is useful to consider concrete scenarios in which AI-generated financial disclosures are already emerging in practice. In a first scenario, an international bank integrates a GenAI assistant into its consolidated reporting platform. Controllers upload trial balances and management packs, and the tool produces a first draft of the segment-level MD&A based on preconfigured templates and prior-year language. Then, people go over the draft, change the tone, get rid of extra text, and add discussions of risks that are specific to the entity. In this case, the AI output is mostly used to help people get more done. The biggest risks to reliability are made-up explanations or not mentioning recent changes in the law. If the bank has good review controls and keeps track of all AI interactions, the remaining risk might be low and be balanced out by fewer transcription errors.

In the second case, a smaller listed company that doesn't have a very advanced reporting system uses a cloud-based disclosure management platform that comes with GenAI built in. Management depends a lot on the AI tool to write risk factor disclosures and forward-looking statements because there aren't many employees. Human review mostly looks at formatting, and there isn't much documentation of prompts, data sources, or model versions. The risk of using AI is much higher here than it is in other places. Auditors might have trouble connecting important statements to the evidence that backs them up. Also, governance bodies might not be able to tell which parts of the story were written by AI and which parts were written by people. The same technology can have very different levels of reliability, depending on how it is used in processes and oversight structures.

A third situation is ESG and sustainability reporting, which requires combining a lot of qualitative data. More and more organizations are using GenAI to summarize climate risk assessments, stakeholder engagement results, or supply chain due diligence activities. These stories often use different kinds of information, like site reports, questionnaires, and databases from outside sources. If data curation isn't done carefully, AI-generated sustainability disclosures could make it seem like risk management practices are more advanced than they really are or make it hard to tell the difference between planned and actual actions. From an audit standpoint, these situations necessitate specific procedures concerning the correlation between foundational evidence and overarching AI-generated assertions, especially when disclosures could affect investors' views on long-term risk.

Table 1: Comparison of Reliability Dimensions: Human-Written vs. AI-Generated Disclosures

Reliability dimension	Human-written disclosures	AI-generated disclosures	Comments
Accuracy vs. underlying data	Dependent on manual processes; susceptible to transcription and copying errors, especially under time pressure.	It can be tightly linked to underlying data, reducing transcription errors, but is prone to hallucinations if not grounded or if prompts are poor.	Vendors highlight anomaly detection and data-driven drafting; regulators warn about hallucinations and data provenance issues [2–4].

Reliability dimension	Human-written disclosures	AI-generated disclosures	Comments
Completeness	Driven by management judgment and checklists, risk of omission bias or boilerplate disclosure.	Can systematically benchmark against peer disclosures and regulatory checklists, but may replicate historical biases and omit novel entity-specific issues.	Disclosure platforms emphasize benchmarking; generative models tend to reproduce historical patterns [3,8,17].
Neutrality/bias	Subject to managerial incentives and strategic tone.	May reduce idiosyncratic stylistic bias but can encode systematic optimism or boilerplate tone from training data or prompts.	Research on disclosure tone and media suggests models trained on historical text inherit biases [17].
Consistency across periods and sections	Relies on human discipline; inconsistencies in terminology and cross-references are common.	Strong at maintaining template-based consistency in terminology, structure, and cross-referencing when properly configured.	Practitioner reports and surveys find that AI improves process standardization in reporting [2,16].
Verifiability and auditability	Source files and drafts can be archived; reasoning often implicit and undocumented.	Requires explicit logging of prompts, inputs, model versions, and outputs to be auditable; black-box systems hinder verification.	PCAOB and oversight bodies stress audit trails, versioning, and human sign-off for AI outputs [3,4,6].

4. Regulatory and Governance Context

4.1 Regulatory scrutiny of AI in financial reporting and auditing

More and more, regulators are realizing that AI and LLMs are changing how financial reports are written. The PCAOB's 2024 staff spotlight talks about how they talked to auditors and issuers about integrating GenAI and makes it clear that the current standards still apply. Auditors need to look at AI-related risks, evaluate controls, and get enough appropriate audit evidence about AI-generated information [4]. The SEC has made it clear that companies are still responsible for the accuracy of claims about AI capabilities and that AI use in financial reporting or investment situations must be accompanied by the right controls and disclosures [3].

The European Union’s AI Act treats many financial applications as high-risk, requiring transparency, documentation, and governance, while European securities regulators have signalled interest in AI’s role in corporate reporting, especially narrative ESG disclosures [3,12]. The IAASB has issued a technology position describing its plans to integrate technology considerations, including AI, into standards and guidance [12].

4.2 AI governance and internal control over financial reporting

KPMG’s 2024 survey indicates that organisations with more mature AI capabilities are significantly more likely to have formal AI governance frameworks, AI controls assurance, and board-level oversight [16]. Best-practice guidance emphasizes purpose-specific policies, robust data governance, model governance (including validation, monitoring, and versioning), human-in-the-loop review, and comprehensive audit trails [2–4,12,16].

From an ICFR perspective, AI-based disclosure processes can be viewed as a combination of IT-dependent manual controls and automated controls. Auditors must therefore consider them in risk assessment and test both general IT controls and application-level controls, in line with ISA 315 and related guidance [6,12–14].

4.3 Auditing standards and AI-driven processes

Existing auditing standards provide a basis for dealing with AI-driven disclosure workflows. ISA 315 (Revised 2019) requires auditors to understand the entity’s system of internal control and to identify and assess risks of material misstatement, including those arising from IT and automated tools [6]. ISA 330 requires the auditor to design and implement responses to assessed risks, including tests of controls and substantive procedures [13]. ISA 230 on audit documentation applies to the auditor’s use of automated tools and techniques, including AI, and regulators have issued guidance on documenting their use [14]. National standard setters, such as AUASB and professional bodies, have issued technology updates and ISA 315 implementation guidance that explicitly mention AI and machine learning as factors auditors must consider [14,15].

5. Conceptual Framework for Reliability of AI-Generated Disclosures

To structure the analysis, this paper proposes a four-layer framework that links (1) AI system design and data; (2) process and control arrangements; (3) governance and oversight; and (4) independent assurance by external auditors. Each layer contributes to the overall reliability of AI-generated disclosures [4,6,12,16].

At the AI system and data layer, reliability depends on training data quality, domain adaptation, grounding to internal data, and security and privacy controls. At the process and control layer, disclosure workflows, data lineage, logging, version control, and human review are central. Governance and oversight involve AI strategy, risk appetite, board and audit committee oversight, and regulatory communication. Finally, external auditors provide independent assurance by understanding AI use, evaluating controls, and performing substantive procedures responsive to AI-related risks.

5.1 Comparison with earlier waves of audit technology

The emergence of GenAI echoes earlier waves of audit technology, such as electronic working papers, computer-assisted audit techniques, robotic process automation, and machine learning–based anomaly detection. In each wave, audit firms and standard setters initially focused on whether existing standards were flexible enough to accommodate new tools, and then developed practice-oriented guidance on how to design procedures and documentation. The experience with data analytics and automation suggests that technology rarely replaces core professional judgments; instead, it reshapes them by altering the information set that auditors can efficiently examine [10,11,19].

However, GenAI differs from earlier technologies along at least two dimensions. First, it operates at the level of language rather than raw data, and therefore has the potential to influence not only how auditors analyse information but also how they formulate audit documentation, client queries, and even suggested disclosure language. Second, GenAI outputs tend to be perceived as highly fluent and human-like, which may encourage overreliance. Experimental studies in psychology and information systems demonstrate that users are more inclined to accept recommendations articulated in confident and coherent prose, regardless of their accuracy. This "automation bias" is especially important when AI is used to write or check qualitative disclosures. The framework proposed in this paper prioritizes explainability, logging, and explicit human approval, which are essential safeguards against the uncritical acceptance of AI-generated narratives.

6. Audit Procedures for AI-Generated Financial Disclosures

A risk-based methodology may be employed to formulate audit procedures for disclosures created by artificial intelligence. First, auditors perform risk assessment procedures by mapping where AI is used, understanding models and data sources, and assessing the control environment [6,12,14,19]. Second, they evaluate the design and implementation of AI-related controls, including AI governance policies, system configuration, user access controls, data lineage controls, and human review.

Where reliance on controls is planned, auditors test operating effectiveness by sampling AI-generated disclosure items and tracing review and approval history, verifying prompt and data logging, and confirming that exceptions and anomalies are investigated. Empirical and survey evidence suggest that AI can increase audit quality when controls are robust, but may compromise due to professional care if auditors rely uncritically on AI outputs [1,9–11,19].

Substantive procedures on AI-generated narratives should include data-consistency checks against audited financial statements, cross-period and peer benchmarking using text analysis tools, fact-checking of high-risk statements, and testing for generic boilerplate and hallucination indicators. Auditors should document AI use, identify risks, the results of tests of controls and substantive procedures, and any AI-related deficiencies in ICFR. To operationalise these ideas, Table 2 maps specific AI risks (such as hallucination, omission, and bias) to related audit assertions and example procedures. Figure 2 graphically contrasts inherent AI-related risk levels with the strength of typical controls across key risk categories.

Table 2: AI-Related Risks and Illustrative Audit Procedures for Narrative Disclosures

AI-related risk	Affected assertions/objectives	Illustrative audit procedures
Hallucinated or fabricated statements	Accuracy, occurrence, compliance	Identify material AI-generated narrative sections; reconcile key statements to underlying evidence; search for references to non-existent items [3–5,7].
Omission of entity-specific risks	Completeness, neutrality	Compare AI-generated risk disclosures with prior-year human ones and peer group; review board and risk committee minutes to identify missing risks [2,3,16].
Biased or overly promotional tone	Neutrality, faithful representation	Use sentiment and readability analysis to detect extreme optimism; discuss with management; review against underlying performance and independent sources [17].
Weak AI governance and a lack of logging	Auditability, traceability	Inspect AI logs and governance documentation; test whether prompts, data sources, and outputs are recorded; assess impact on audit evidence [3,4,6,12,14].

7. Discussion and Future Research Directions

The evidence reviewed suggests that AI-generated disclosures can enhance consistency and alignment with underlying data when models are properly grounded and embedded in robust control environments. Studies on AI-refined texts and AI-enabled auditing show improved predictive performance and quality indicators [1,8,10,18,19]. However, this potential is conditional on high-quality data, robust ICFR and AI-specific controls, strong governance, and transparent audit trails. Figure 1 provides an illustrative comparison of relative reliability scores for human-written and AI-generated disclosures across the main dimensions discussed above.

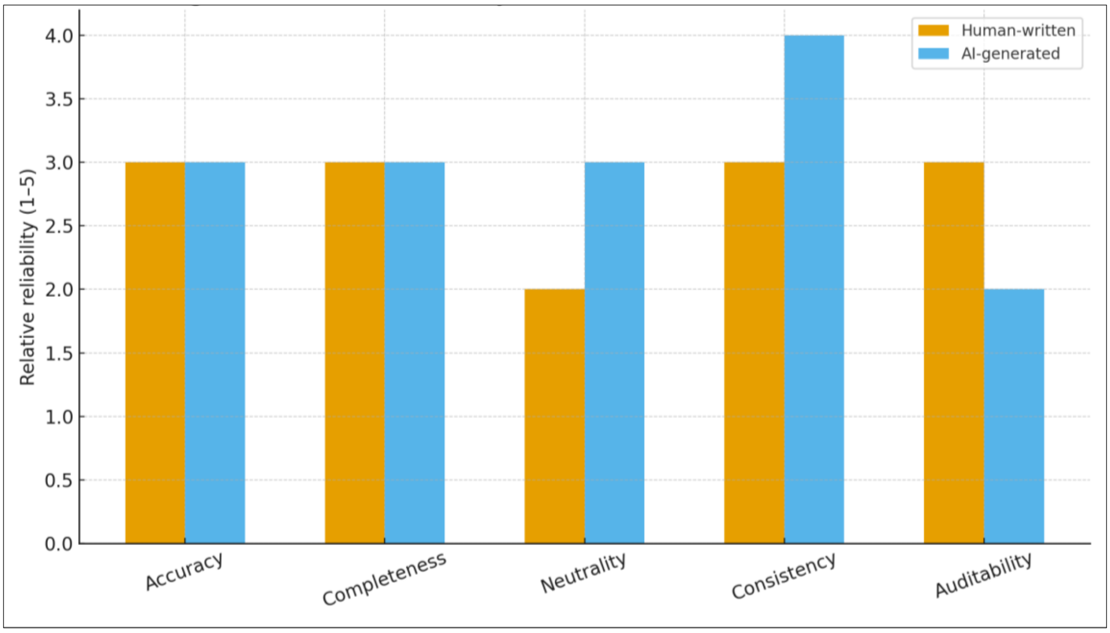

Figure 1: Simple comparative graph showing relative reliability scores for human vs. AI-generated disclosures by dimension

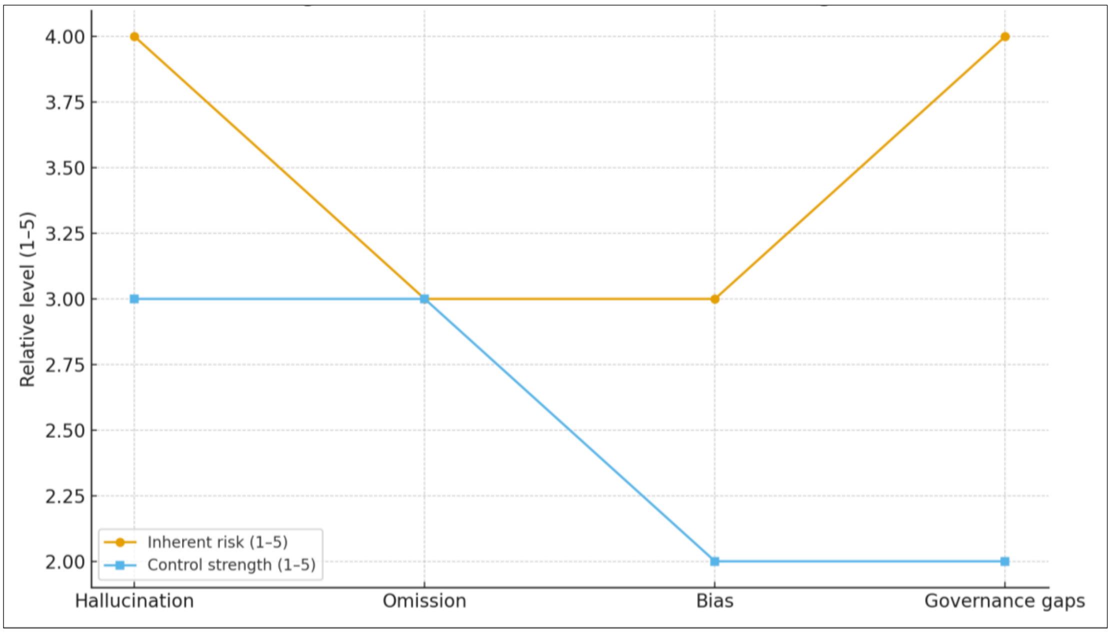

Figure 2: Graph showing inherent AI-related risk levels vs. control strength for key risk categories (hallucination, omission, bias, governance gaps)

Standard setters may wish to clarify expectations for documenting AI use in financial reporting and auditing, and to provide explicit examples of AI-related risks and procedures in application guidance. Regulators are already signalling that disclosure of AI use and auditability of AI workflows will become increasingly important [3–7,12].

Future research could directly compare AI-generated and human-written disclosures on measures of readability, tone, information content, and misstatement risk; examine how investors and analysts react to AI-generated disclosures; study how AI governance structures affect financial reporting and audit outcomes; and analyze how auditors' own use of AI tools in reviewing AI-generated disclosures influences audit quality and efficiency.

7.1 Implications for emerging markets and small and medium-sized entities

The implications of AI-generated disclosures are likely to be especially pronounced in emerging markets and among small and medium-sized entities (SMEs). On one hand, GenAI tools can help such entities overcome resource constraints by providing access to sophisticated drafting and benchmarking capabilities that were previously limited to large corporations. A mid-sized manufacturer listed on a regional exchange may utilize GenAI to analyze peer disclosures in global markets and synchronize its own narrative with current terminology and regulatory standards. This may improve comparability and mitigate the risk of SMEs unintentionally omitting critical information due to the absence of specialized disclosure counsel.

Conversely, entities in emerging economies may encounter increased risks. They may lack strong IT governance, autonomous risk-management procedures, or proficient audit committees capable of supervising AI implementations. The legal and regulatory frameworks governing AI utilization may be underdeveloped, resulting in ambiguity for preparers concerning expectations related to transparency, data protection, and liability. External auditors operating in such contexts may need to exert additional effort in instructing clients on AI control mandates, while simultaneously safeguarding against scope creep that encroaches upon management's responsibilities. Professional organizations in these jurisdictions can significantly contribute by providing practical recommendations, case studies, and training resources adapted to local circumstances.

Moreover, SMEs frequently depend on standardized cloud solutions instead of customized systems. When these solutions include GenAI modules, configuration choices made by vendors—such as default prompts, model selection, and logging policies—can directly influence disclosure outputs and auditability. Regulators and standard setters may therefore wish to engage with software vendors that serve SME markets, encouraging them to embed minimum control and transparency features that support both preparers and auditors.

7.2 Limitations and avenues for future research

As a conceptual and narrative review, this paper has several limitations. First, it relies on a combination of early empirical studies, practitioner surveys, and regulatory commentaries, many of which are based on limited samples or pilot implementations of AI tools. The landscape of GenAI applications in financial reporting is evolving rapidly, and specific tools discussed in current industry reports may look very different in a few years. Future research should therefore update and refine the framework as more rigorous and large-sample evidence becomes available.

Second, the paper treats "AI-generated disclosures" as a broad category, whereas in practice, there is a spectrum ranging from minor GenAI-assisted edits to fully automated drafting of entire sections. The reliability and audit implications will differ across this spectrum, as will the appropriate combination of controls and procedures. Empirical studies that distinguish between levels of AI involvement could shed light on which combinations of human and machine input yield the best balance of quality, efficiency, and cost.

Third, the framework is primarily oriented toward traditional financial statements and related narrative sections. Yet AI is also being deployed in integrated reporting, sustainability reporting, tax reporting, and regulatory filings outside the financial statements. Each of these domains may include distinct risk profiles and legal obligations. Climate and sustainability disclosures frequently encompass scenario analysis, extended timeframes, and scientific uncertainty, which may interact with the strengths and shortcomings of GenAI in unique ways. Future research may expand the framework to these areas and investigate if specific categories of AI-generated knowledge necessitate distinct assurance methodologies, such as limited assurance or agreed-upon methods.

The analysis herein concentrates on the supply aspect of disclosures. There exists a demand-side aspect: as investors, analysts, regulators, and other stakeholders increasingly utilize AI tools to process and understand disclosures, the broader information landscape will mirror the interplay between AI-generated reports and AI-driven analyses. Comprehending the impact of these feedback loops on market efficiency, risk pricing, and trust in financial reporting is a significant research frontier for interdisciplinary collaboration among accounting, finance, computer science, and law.

8. CONCLUSION

GenAI is swiftly revolutionizing financial disclosure methodologies. Although AI-generated narrative disclosures provide considerable efficiency and consistency advantages, they also pose dangers associated with hallucinations, prejudice, and a lack of transparency. Current research from auditing and finance suggests that AI can improve financial reporting and audit quality when integrated into strong governance and control systems, but may compromise dependability in the absence of such frameworks or when they are inadequate.

This article synthesizes recent academic and practitioner literature to compare AI-generated and human-written disclosures across key reliability characteristics and to delineate a risk-based framework of audit processes for AI-enabled reporting contexts. A multi-tiered framework connects AI system design, controls, governance, and independent assurance, proposing actionable measures for auditors to address AI-related risks within established standards like ISA 315 and ISA 330. Preparers should regard GenAI as a potent yet hazardous instrument rather than an independent creator; auditors and regulators have the task of modifying techniques and advice to harness AI's advantages while ensuring faithful representation, auditability, and accountability are not compromised.

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