

Artificial Intelligence in Audit Processes: Opportunities and Risks for Public Accountability

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Abstract

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This study examines the integration of artificial intelligence (AI) in audit processes, with a focus on its opportunities and risks for public accountability. The main question centers on how AI can enhance audit effectiveness while safeguarding transparency and ethical standards. Employing a systematic literature review approach, the study synthesizes peer-reviewed evidence from diverse disciplines to assess the technological applications, efficiency gains, and governance implications of AI in auditing. The analysis reveals that AI offers significant benefits in automating audit tasks, improving data accuracy, and detecting irregularities, yet it also introduces risks related to algorithmic bias, privacy concerns, and regulatory gaps. Discussion of the reviewed literature highlights thematic patterns and policy considerations, emphasizing the importance of institutional readiness and ethical oversight. The findings suggest that balanced governance frameworks are essential to harness AI's potential while maintaining accountability in both public and private sector audits.

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1. Introduction

Artificial intelligence (AI) is reshaping how auditors plan, execute, and report on engagements, promising step-changes in coverage, speed, and insight. In financial statement audits, AI and adjacent techniques such as big data analytics and process mining enable full-population testing, anomaly detection, and continuous monitoring, capabilities long theorized but only recently practical at scale (Cao et al., 2015; Appelbaum et al., 2017). Within firms, these tools are being woven into intelligent process automation, combining machine learning with robotic process automation (RPA) to streamline routine procedures and free auditors to focus on higher-order judgments (Moffitt et al., 2018; Parker, 2019). The trajectory extends well beyond the private sector: public audit bodies face intensifying expectations to deliver timely assurance and evaluative insight on complex programs, positioning AI as a strategic lever for public accountability and value creation (Cordery & Hay, 2022; Volodina & Grossi, 2024).

Yet AI's promise is inseparable from risks that cut to the core of audit credibility and democratic accountability. Accuracy and efficiency gains may be offset by opacity in model design and training data, creating challenges for explainability, contestability, and due process, especially where audit conclusions affect citizens and public services (Busuioc, 2021). A growing body of work argues that in high-stakes settings auditors should prefer inherently interpretable models over black-box systems with post-hoc explanations, to preserve auditee rights and enable meaningful oversight (Rudin, 2019; Gunning & Aha, 2019). Operational risks also loom: automation can embed control weaknesses, propagate data quality problems

at scale, and widen the audit expectation gap if digital outputs are over-trusted or poorly communicated (Fotoh & Lorentzon, 2023).

For the public sector, these concerns intersect with distinctive accountability regimes. Supreme audit institutions and public auditors operate in environments of multiple principals, heterogeneous stakeholders, and statutory mandates. The uptake of AI must therefore be appraised not only for audit efficiency but for its implications for transparency, explainability to lay audiences, and fairness in the evaluation of policies and programs (Busuioc, 2021; Cordery & Hay, 2022). At the same time, the literature highlights tangible opportunities to strengthen accountability: AI-enabled analytics can expand substantive testing of procurement and grants, surface process deviations across entire populations, and provide more timely insights on program performance (Appelbaum et al., 2017). A systematic review is warranted to synthesize this dispersed evidence, map where opportunities have translated into demonstrable audit benefits, and identify governance, methodological, and capability conditions that mitigate risk while enhancing public accountability.

Taken together, the maturing scholarship suggests that AI in auditing is neither a purely technical upgrade nor a wholesale paradigm shift. Rather, it is an institutional choice set, about models, data, controls, and communication, whose consequences are amplified in the public sphere. This review therefore examines peer-reviewed studies from 2015–2024 to assess how AI has been deployed in audit processes, what benefits and harms have been observed, and which design and oversight practices best align innovation with the public interest.

2. Literature Review

The application of artificial intelligence (AI) in auditing has been examined from multiple perspectives, reflecting its multifaceted implications for efficiency, assurance quality, and public accountability. Early studies in the private sector identified AI-driven analytics as transformative for audit methodology, enabling continuous auditing, anomaly detection, and risk assessment at a scale unattainable through traditional sampling (Cao et al., 2015; Appelbaum et al., 2017). Process mining, in particular, has been highlighted as a powerful tool for uncovering irregularities and process deviations in both financial and compliance audits (Imran et al., 2023). These advances have been supported by robotic process automation (RPA) and machine learning, which automate repetitive tasks and facilitate real-time insight generation (Rozario & Thomas, 2019).

In the public sector, AI adoption has been slower but increasingly strategic. Cordery and Hay (2022) note that supreme audit institutions are experimenting with data-driven approaches to evaluate complex public programs, often in response to heightened transparency demands. AI has been applied in areas such as procurement monitoring, performance auditing, and fraud detection, with case studies indicating improved timeliness and coverage (Fotoh & Lorentzon, 2023; Volodina & Grossi, 2024). However, as Busuioc (2021) observes, the opacity of certain AI models raises concerns about explainability and the ability to hold algorithmic outputs accountable in democratic settings.

Scholars have stressed that model interpretability is not only a technical preference but also a governance requirement in high-stakes audits (Rudin, 2019;

Gunning & Aha, 2019). Without transparent logic, AI tools risk eroding stakeholder trust, particularly where audit findings influence policy decisions or public perceptions of institutional integrity. Studies also caution that automation may exacerbate the audit expectation gap if stakeholders misinterpret the role of AI in professional judgment (Kokina & Davenport, 2017; Fotoh & Lorentzon, 2023).

Empirical research has begun to demonstrate AI's measurable impacts on audit quality. A 2022 study found that AI usage is associated with reduced going-concern errors and improved detection of material weaknesses, indicating real gains in audit accuracy and reliability (Fedyk et al., 2022). Conceptual advances also point toward a more integrated future: Leocádio et al. (2024) propose a framework through which AI shifts auditing from retrospective snapshots to proactive, continuous monitoring, redefining the auditor's role within organizational oversight.

Collectively, the literature paints a nuanced picture: AI holds considerable promise for augmenting audit coverage, depth, and responsiveness—but this potential can only be realized if frameworks for interpretability, governance, and institutional alignment are developed in tandem.

3. Methods

This study adopted a systematic literature review (SLR) approach to synthesize peer-reviewed evidence on the use of artificial intelligence (AI) in audit processes, with a particular focus on its opportunities and risks for public accountability published between 2015-2024. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to

ensure transparency and replicability in study selection and analysis. Searches were conducted across major academic databases including Scopus, Web of Science, Google Scholar, and IEEE Xplore. The search strategy combined keywords and Boolean operators such as “artificial intelligence” AND “audit” OR “auditing” AND “public accountability” OR “public sector,” ensuring coverage of both public and private sector audit contexts relevant to governance outcomes.

Inclusion criteria were limited to peer-reviewed journal articles, conference proceedings, and authoritative institutional reports written in English, which provided empirical or conceptual insights into AI applications in auditing. Studies were excluded if they focused solely on non-audit financial technologies, lacked substantive discussion of AI tools, or were non-peer-reviewed commentaries. After initial retrieval, duplicates were removed, and titles, abstracts, and full texts were screened in successive stages. The final set of studies was analyzed thematically, identifying patterns across three dimensions: (1) technological applications of AI in auditing, (2) reported efficiency and quality benefits, and (3) governance and accountability challenges. This structured approach enabled the integration of diverse disciplinary perspectives while maintaining analytical focus on AI’s implications for public accountability.

4. Results and Discussion

Across the reviewed studies, three consistent result patterns emerge. First, AI augments audit coverage and speed by enabling full-population tests, anomaly detection, and process-conformance checks that outperform traditional sampling.

Big data-enabled analytics and process mining surface deviations across entire transaction populations, allowing auditors to reallocate effort toward areas of heightened risk (Cao et al., 2015; Appelbaum et al., 2017). The evidence base also shows that nontraditional, high-volume data—procurement logs, sensor traces, communications metadata, can serve as complementary evidence when evaluated against audit criteria for sufficiency, reliability, and relevance (Yoon et al., 2015). Collectively, these capabilities translate into timelier insights and richer anomaly explanations, particularly when analytics are embedded in continuous auditing workflows.

Second, the literature reports quality benefits but cautions that they are contingent on organizational readiness. Studies of intelligent process automation and RPA indicate cycle-time reductions and fewer manual errors in routines like data extraction, trace-to-source, and control testing (Moffitt et al., 2018; Rozario & Thomas, 2019). At the same time, researchers warn that analytics programs often stall at the “pilot” stage due to data access barriers, model maintenance burdens, and skills gaps. Findings emphasize the need for cross-functional teams (auditors, data engineers, domain specialists) and explicit evidence frameworks to govern how AI outputs are weighted alongside traditional procedures (Kokina & Davenport, 2017; Fotoh & Lorentzon, 2023). A related theme is capability building: auditors require fluency in data provenance, feature engineering, and model limitations to avoid over-reliance on automated flags; otherwise, AI may widen the expectation gap if stakeholders infer “guaranteed” detection (Earley, 2015; Fotoh & Lorentzon, 2023).

Third, public-sector audits face distinctive accountability demands that sharpen both the promise and the risk. Supreme audit institutions are deploying AI for procurement screening, grant monitoring, and performance evaluation, reporting broader coverage and earlier exception alerts relative to purely manual approaches (Cordery & Hay, 2022; Volodina & Grossi, 2024). But because audit conclusions can affect services and citizens, the governance literature argues for “interpretability-first” model choices and for documentation that enables auditees and legislatures to contest and understand findings (Rudin, 2019; Busuioc, 2021). Explainable-AI techniques (e.g., rule extraction, local post-hoc explanations) can aid sense-making, though surveys caution these methods have scope limits and can themselves introduce approximation error; therefore, they should supplement, not replace, inherently interpretable models in high-stakes audits (Guidotti et al., 2018; Rudin, 2019).

Synthesizing these results, the discussion points to governance mechanisms that convert technical potential into accountable practice. Data governance needs to be formalized around lineage, quality thresholds, consent/privilege boundaries, and retention, conditions that affect both model performance and the legal defensibility of audit evidence. Model risk management should include prerelease validation against known cases, drift monitoring, adversarial challenge sessions, and periodic “audit of the algorithm”, with workpapers capturing training data, feature sets, hyperparameters, and versioning (Fotoh & Lorentzon, 2023). Communication protocols matter: when reports draw on AI outputs, auditors should disclose model

roles, known limitations, and human review steps to maintain trust with nonspecialist stakeholders (Busuioc, 2021; Cordery & Hay, 2022).

For practice, three design principles recur. Interpretability-first: prefer transparent models (e.g., sparse linear rules, monotonic gradient-boosting with constraints) where they achieve comparable accuracy; supplement with XAI only when complexity is essential (Guidotti et al., 2018; Rudin, 2019). Human-in-control: embed escalation paths so auditors interrogate outliers, revisit thresholds, and override automation with documented rationale, minimizing automation bias (Kokina & Davenport, 2017). Evidence-coherence: triangulate AI indicators with traditional procedures and domain knowledge to meet sufficiency and appropriateness standards; here, the “complementary evidence” framing helps disciplined aggregation of signals (Yoon et al., 2015; Appelbaum et al., 2017). Implemented together, these practices enable institutions to capture efficiency and coverage gains while reinforcing, rather than diluting the transparency, contestability, and fairness that underpin public accountability.

5. Conclusion

The findings of this review indicate that artificial intelligence is steadily transforming audit processes, offering substantial opportunities to enhance efficiency, accuracy, and fraud detection capabilities in both public and private sector contexts. By automating routine tasks, enabling advanced data analytics, and supporting real-time risk assessment, AI has the potential to strengthen transparency and reinforce public accountability. However, these benefits are counterbalanced by

notable risks, including algorithmic bias, lack of interpretability, data privacy concerns, and the need for new regulatory frameworks to safeguard ethical standards. The evidence suggests that the successful integration of AI into auditing requires not only technological readiness but also institutional capacity to ensure accountability in decision-making.

Overall, the review underscores the need for balanced policy approaches that encourage innovation while mitigating potential harms. Capacity-building programs for auditors, cross-sector collaboration, and the development of ethical AI standards emerge as critical priorities. Future research should focus on longitudinal and comparative studies to assess the real-world impact of AI adoption in auditing, particularly in public sector contexts where accountability to citizens is paramount. By aligning technological advancement with robust governance frameworks, AI in auditing can move beyond efficiency gains to become a powerful enabler of public trust and fiscal integrity.

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