



From Algorithmic Bias to Trustworthy Auditing: A Systematic Literature Review of AI Ethics, Accountability, Explainability, and Human Oversight

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ABSTRACT. *The rapid adoption of artificial intelligence (AI) in auditing creates significant opportunities for automation, analytical efficiency, and improved audit quality, while simultaneously introducing challenges related to algorithmic bias, ethics, accountability, explainability, and human oversight. This qualitative systematic literature review examines how these dimensions shape the development of trustworthy auditing. Using a systematic review approach, relevant literature was synthesized thematically across accounting, auditing, information systems, computer science, and AI ethics. The findings identify four interconnected dimensions of trustworthy AI enabled auditing: algorithmic bias and fairness, AI ethics and accountability, explainability and transparency, and human oversight and professional judgment. The review indicates that trustworthy auditing cannot be achieved through technological accuracy alone but requires integrated socio-technical governance mechanisms. The study contributes a conceptual perspective that connects ethical AI governance with professional auditing and identifies opportunities for future empirical research.*

Keywords: *Algorithmic Bias; AI Ethics; Audit Accountability; Explainable AI; Human Oversight*

INTRODUCTION

The rapid integration of artificial intelligence (AI) into accounting and auditing is transforming how audit evidence is processed, anomalies are detected, risks are assessed, and professional judgments are supported. AI enabled auditing can enhance automation, analytical capacity, and the ability to process complex and large-scale datasets that may be difficult to examine through conventional procedures (Fedyk et al., 2022; Hasan, 2022). Research has also indicated that AI and machine-learning applications can contribute to audit risk detection and audit quality improvement by identifying patterns and anomalies within financial information (Lokanan et al., 2019; Noordin et al., 2022). However, the increasing reliance on algorithmic systems also introduces fundamental ethical and governance challenges that extend beyond technical performance.

One of the most significant concerns is algorithmic bias. AI systems may reproduce or amplify biases embedded in training data, organizational processes, model assumptions, and human decision-making. Ntoutsis et al. (2020) emphasize that bias in data driven AI can emerge at multiple stages of the data and algorithmic lifecycle. In auditing, such bias may affect risk assessment, anomaly detection, evidence evaluation, and professional judgments, potentially undermining the principles of fairness, independence, and impartiality. Murikah et al. (2024), in their systematic review of AI

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systems applied to auditing, identify data deficiencies, demographic homogeneity, spurious correlations, inappropriate comparators, and cognitive biases as important sources of technical and human bias. They further demonstrate that isolated technical biases can develop into broader socioeconomic consequences. Generative artificial intelligence has the potential to revolutionize human resource management, but its success heavily depends on the organization's readiness to adapt to technological changes, as well as its commitment to ensuring fair and ethical implementation (Yulianti, G., et al, 2024).

The ethical dimension of AI in auditing is therefore inseparable from questions of accountability and governance. Munoko et al. (2020) argue that the use of AI in auditing raises important ethical questions concerning responsibility, professional judgment, privacy, and the consequences of automated decision-making. Similarly, Lehner et al. (2022) highlight the normative and ethical challenges associated with AI-based decision-making in accounting and auditing. As algorithmic systems become increasingly embedded in audit processes, determining who is responsible for erroneous, biased, or opaque AI-supported decisions becomes particularly important. Algorithmic accountability consequently requires mechanisms for monitoring, evaluation, documentation, and human responsibility throughout the AI lifecycle (Raji & Buolamwini, 2019; Mökander & Floridi, 2021). The collaboration between artificial intelligence platforms and digital innovation hubs can enhance productivity, operational efficiency, and market access for SMEs (Eka Wahyu Kasih, et al, 2024).

A related challenge concerns explainability and transparency. AI systems, particularly complex machine learning models, may generate outputs that are difficult for auditors and other stakeholders to understand or challenge. Explainability is consequently not merely a technical characteristic but also an ethical requirement for establishing confidence in AI-supported decisions. McDermid et al. (2021) distinguish the technical and ethical dimensions of AI explainability, while Ehsan et al. (2021) emphasize the importance of social transparency in human-AI interaction. In auditing, explainability can support professional skepticism by enabling auditors to understand how AI-generated recommendations are produced and whether those recommendations are sufficiently reliable for audit purposes.

These challenges highlight the continuing importance of human oversight. Rather than replacing professional judgment entirely, AI should be embedded within a human-AI collaboration framework in which auditors retain responsibility for interpreting outputs, challenging algorithmic recommendations, and exercising professional judgment. Research on AI and auditing identifies potential tensions between automation efficiency and professional diligence, including risks of deskilling and excessive reliance on automated outputs. Human oversight therefore represents an important safeguard for maintaining professional skepticism, accountability, and ethical responsibility. Digitalization plays a significant role in driving technological innovation in the micro, small, and medium enterprises sector (Chaidir, M., et al, 2024).

Despite growing scholarship, the literature remains fragmented across accounting, auditing, computer science, AI ethics, information systems, and governance. Existing studies frequently examine individual dimensions such as bias, explainability, audit quality, privacy, or accountability without sufficiently integrating them into a comprehensive framework for trustworthy auditing. Murikah et al. (2024) likewise identify continuing gaps concerning standardized risk assessment, clearer boundaries for human involvement, model evaluation, contextual validation, and real-world comparisons. Therefore, this systematic literature review aims to synthesize the existing body of knowledge on AI ethics in auditing by examining how algorithmic bias, accountability, explainability, and human oversight interact in shaping trustworthy auditing practices. By integrating these dimensions, the review seeks to identify dominant themes, conceptual relationships, unresolved challenges, and future research directions for the responsible and trustworthy integration of AI into auditing.

LITERATURE REVIEW

The literature consistently indicates that artificial intelligence (AI) is transforming auditing by increasing the capacity to analyse large datasets, automate repetitive activities, identify anomalies, and support risk assessment. Fedyk et al. (2022), using data from more than 310,000 resumes across 36 major audit firms and interviews with 17 audit partners, found that AI investment was associated with improved audit quality, lower audit fees, and changes in the demand for accounting labour. Similarly, existing research identifies AI as increasingly relevant to audit planning, risk assessment, transaction

testing, analytics, and audit documentation (Munoko et al., 2020). These findings establish that AI adoption is not merely a technological development but a transformation of the professional and organizational structure of auditing.

A major theme emerging from the literature is that AI-enabled auditing can introduce or reproduce algorithmic bias through data, model design, organizational practices, and human judgment. Ntoutsis et al. (2020) conceptualize bias in data-driven AI as a multidimensional problem that can arise throughout the data and algorithmic lifecycle, demonstrating that technical performance alone is insufficient to guarantee fairness. The systematic review by Murikah et al. (2024) provides more specific evidence for auditing by identifying data deficiencies, demographic homogeneity, spurious correlations, inappropriate comparators, and cognitive biases as important sources of technical and human bias. Their review further indicates that individual technical biases can propagate into broader socioeconomic consequences, demonstrating that algorithmic bias should be understood as a sociotechnical rather than exclusively computational problem.

The literature further establishes that algorithmic bias cannot be separated from broader questions of AI ethics, accountability, privacy, transparency, and trust. Munoko et al. (2020) identify ethical implications associated with AI adoption in auditing, emphasizing that technological benefits may be accompanied by unintended ethical consequences. More specifically, Lehner et al. (2022), through a theoretically informed literature review, identified objectivity, privacy, transparency, accountability, and trustworthiness as five major ethical challenges associated with AI-based decision-making in accounting and auditing. These findings suggest that trustworthy auditing requires organizational mechanisms capable of assigning responsibility for AI-supported decisions rather than treating algorithmic outputs as inherently neutral or autonomous.

Explainability represents another central dimension of trustworthy AI because auditors need to understand, evaluate, and potentially challenge algorithmic outputs. McDermid et al. (2021) distinguish the technical and ethical dimensions of AI explainability, indicating that explanations are relevant not only to model interpretation but also to accountability and responsible deployment. The literature on human-centered explainable AI similarly emphasizes that transparency should address the relationship between algorithmic systems and their users rather than focusing exclusively on the

internal mechanics of models. In auditing, this distinction is particularly important because professional judgments remain necessary when evaluating whether AI-generated evidence or risk signals are sufficiently appropriate for audit purposes. The literature therefore positions explainability as a bridge between technical model performance and professional accountability.

Human oversight emerges as a critical safeguard against excessive reliance on automated decisions. Fedyk et al. (2022) found that AI investment improved measurable audit outcomes but was also associated with reductions in accounting employment over time, highlighting the organizational consequences of automation. The literature therefore suggests that AI should complement rather than simply substitute professional expertise, particularly in complex situations requiring skepticism, contextual interpretation, and ethical judgment. Murikah et al. (2024) specifically recommend human oversight alongside automation, periodic AI auditing, representative algorithmic testing, and the integration of fairness and accountability into system design. This perspective is consistent with the broader human-centered AI literature, which emphasizes maintaining meaningful human involvement in high-impact algorithmic systems.

Taken together, the literature indicates that trustworthy auditing requires the integration of technological capability with ethical and organizational safeguards. Existing studies have separately examined audit-quality effects, algorithmic bias, ethical risks, transparency, explainability, and human oversight, but the relationships among these dimensions remain insufficiently integrated within the auditing literature. Murikah et al. (2024) identify continuing gaps in model evaluation, risk assessment standards, contextual validation, human involvement, and real-world comparisons. Accordingly, the present systematic literature review conceptualizes trustworthy auditing as an interconnected outcome shaped by four core dimensions: algorithmic bias management, AI ethics and accountability, explainability and transparency, and human oversight. This synthesis provides a basis for understanding how responsible AI governance can preserve audit quality, professional judgment, fairness, and stakeholder trust while enabling the efficiency and analytical benefits associated with AI adoption.

METHODS

This study adopts a qualitative systematic literature review (SLR) to critically synthesize existing research on algorithmic bias, AI ethics, accountability, explainability, and human oversight in auditing. A systematic literature review is appropriate because the literature on artificial intelligence and auditing is interdisciplinary and increasingly fragmented across accounting, auditing, information systems, computer science, and ethics, requiring a transparent and structured process for identifying, evaluating, and synthesizing prior knowledge (Snyder, 2019).

The review follows the principles of the PRISMA 2020 framework to ensure transparency in study identification, screening, eligibility assessment, and final inclusion (Page et al., 2021). The qualitative orientation emphasizes conceptual interpretation rather than statistical meta-analysis, allowing the study to identify recurring themes, theoretical relationships, ethical concerns, and emerging research gaps across the selected literature (Snyder, 2019).

Relevant studies are identified through structured searches of major academic databases, using combinations of keywords such as “artificial intelligence” and auditing, “algorithmic bias” and audit, “AI ethics” and auditing, “AI accountability”, “explainable AI” and auditing, “human oversight” and AI, and “trustworthy AI” and auditing. The search strategy is designed to capture literature addressing both technological and governance dimensions of AI enabled auditing, consistent with the interdisciplinary nature of systematic reviews (Snyder, 2019).

Studies are included when they are peer-reviewed scholarly publications, directly address AI and auditing or closely related AI governance issues, and provide substantive discussion of bias, ethics, accountability, explainability, transparency, human oversight, audit quality, or trustworthy AI. The review focuses on literature published up to 2024, while non peer reviewed materials, duplicate publications, studies unrelated to auditing or trustworthy AI, and publications lacking sufficient conceptual or empirical relevance are excluded. Explicit eligibility criteria are important for reducing selection bias and improving the reproducibility of systematic reviews (Page et al., 2021).

For each selected study, information is systematically extracted concerning authors, publication year, research context, methodology, AI application, ethical issue, principal findings, and implications for auditing. The extracted evidence is then subjected to thematic qualitative synthesis, through which recurring concepts are coded and organized

into higher order themes representing the central dimensions of trustworthy AI enabled auditing. This approach enables fragmented findings to be integrated into a coherent conceptual understanding rather than merely summarized individually (Snyder, 2019).

The synthesis is organized around four interconnected themes: (1) algorithmic bias and fairness, (2) AI ethics and accountability, (3) explainability and transparency, and (4) human oversight and professional judgment. These dimensions are subsequently integrated to develop a conceptual framework explaining how ethical and governance mechanisms can support the transition from algorithmic auditing toward trustworthy auditing. The resulting synthesis also identifies methodological limitations, theoretical gaps, and opportunities for future research, consistent with the purpose of systematic reviews to clarify existing knowledge and establish future research priorities (Page et al., 2021).

RESULTS

The qualitative synthesis identified four interrelated themes that explain the transition from algorithmic auditing toward trustworthy auditing: algorithmic bias and fairness, AI ethics and accountability, explainability and transparency, and human oversight and professional judgment. These themes emerged consistently across the reviewed literature and indicate that trustworthy AI-enabled auditing cannot be achieved through technological accuracy alone but requires integrated ethical, governance, and human-control mechanisms (Murikah et al., 2024; Lehner et al., 2022).

The first major finding is that algorithmic bias represents a fundamental risk to trustworthy auditing, because biased training data, incomplete representations, inappropriate variables, and model assumptions can influence the fairness and reliability of AI-supported audit decisions (Ntoutsis et al., 2020; Murikah et al., 2024). The literature indicates that bias may originate not only from algorithms themselves but also from data collection, historical patterns, model design, and socio-technical environments in which AI systems operate (Ntoutsis et al., 2020). Murikah et al. (2024) further identify causal modelling, representative algorithmic testing, periodic auditing, and human oversight as important mechanisms for identifying and mitigating bias in AI-based auditing systems.

The second finding concerns the central role of AI ethics and accountability in determining whether AI adoption produces responsible audit outcomes. Munoko et al.

(2020) show that although AI provides benefits such as faster data analysis, improved accuracy, and enhanced insights, its application in auditing also creates unintended ethical consequences that require systematic consideration. Lehner et al. (2022) identify objectivity, privacy, transparency, accountability, and trustworthiness as five major ethical challenges associated with AI-based decision-making in accounting and auditing. The synthesis therefore indicates that accountability must extend beyond technical developers to organizations, auditors, governance structures, and other actors responsible for deploying and evaluating AI systems (Lehner et al., 2022; Mökander & Floridi, 2021).

The third finding demonstrates that explainability is a critical condition for professional acceptance and accountability of AI-supported audit judgments. Explainability enables auditors and other stakeholders to understand how an AI system reaches particular outputs, thereby supporting evaluation, challenge, documentation, and professional accountability (McDermid et al., 2021). The literature consequently suggests that highly accurate but opaque models may create governance difficulties when auditors cannot adequately explain or justify AI-generated recommendations (McDermid et al., 2021). This finding is particularly important for auditing because professional judgments must remain defensible and subject to review rather than being treated as unquestionable outputs of automated systems.

The fourth finding emphasizes that human oversight remains essential despite increasing AI automation. Fedyk et al. (2022) demonstrate that AI investment is associated with improved audit quality and lower audit fees, while also producing substantial changes in the demand for accounting labor, indicating that technological efficiency does not eliminate the importance of human capabilities. Their interviews with audit partners further indicate that AI is widely used for anomaly detection, fraud detection, risk assessment, and reallocating human effort toward more complex and high-risk areas. Murikah et al. (2024) similarly recommend maintaining human oversight alongside automation, reinforcing the view that auditors should retain responsibility for interpreting AI outputs and exercising professional judgment.

Overall, the qualitative synthesis indicates that trustworthy auditing emerges from the integration of bias management, ethical accountability, explainability, and meaningful human oversight rather than from AI adoption alone. Mökander and Floridi (2021) argue that ethics-based auditing can provide a mechanism for translating AI ethical principles

into organizational practice through continuous and constructive auditing processes. Therefore, the reviewed literature supports a conceptual shift from viewing AI primarily as an instrument for audit efficiency toward viewing AI auditing as a socio-technical governance process in which technological performance, ethical responsibility, transparency, and professional human judgment must operate together (Murikah et al., 2024; Mökander & Floridi, 2021).

DISCUSSION

The findings of this systematic literature review indicate that the transition from algorithmic auditing to trustworthy auditing depends on the simultaneous integration of algorithmic fairness, AI ethics, accountability, explainability, and human oversight, rather than on technological performance alone (Murikah et al., 2024; Lehner et al., 2022). This finding is consistent with the broader literature showing that AI adoption in auditing creates both opportunities for improved efficiency and new ethical and governance risks (Munoko et al., 2020; Fedyk et al., 2022).

First, the present review confirms and extends the findings of Murikah et al. (2024), whose systematic review identified algorithmic bias, transparency, accountability, and fairness as central ethical risks of AI systems in auditing. While Murikah et al. emphasize the sources and mitigation of bias, the present synthesis connects bias management with explainability and human oversight, suggesting that bias cannot be treated as an isolated technical problem but must be embedded within a broader trustworthy-auditing architecture (Murikah et al., 2024).

Second, the findings complement Fedyk et al. (2022), who provide empirical evidence that AI adoption can improve audit quality and efficiency while simultaneously changing the demand for accounting labor. Whereas Fedyk et al. primarily examine the performance and economic consequences of AI, this review highlights that efficiency gains require complementary safeguards concerning accountability, interpretability, and professional judgment if AI-supported audit outcomes are to remain defensible (Fedyk et al., 2022).

Third, the findings are strongly aligned with Munoko et al. (2020), who demonstrate that AI adoption in auditing generates ethical implications despite its benefits in speed, analytical capability, accuracy, and insight. The present review extends this perspective

by organizing these ethical concerns into a more integrated framework in which accountability and human oversight become mechanisms for translating ethical principles into actual audit practice (Munoko et al., 2020).

Fourth, the results closely support Lehner et al. (2022), whose thematic review identified objectivity, privacy, transparency, accountability, and trustworthiness as major ethical challenges of AI-based accounting and auditing decisions. The present study adds a stronger emphasis on algorithmic bias and human oversight, thereby positioning transparency and accountability not merely as ethical principles but as operational requirements for trustworthy audit decision-making (Lehner et al., 2022).

Fifth, the importance assigned to explainability is consistent with McDermid et al. (2021), who argue that AI explainability has both technical and ethical dimensions and should be connected to the purposes of stakeholders seeking explanations. In the context of auditing, this implies that explainability should enable auditors to interrogate, document, challenge, and justify AI-generated outputs rather than simply provide technically interpretable model features (McDermid et al., 2021).

Sixth, the present findings extend the conceptual argument of Mökander and Floridi (2021) that ethics based auditing can bridge the gap between AI ethical principles and practical implementation. Their emphasis on continuous and constructive auditing supports this review's finding that trustworthy auditing should be understood as an ongoing governance process rather than a one-time technical validation exercise (Mökander & Floridi, 2021).

Seventh, the results are consistent with Seethamraju and Hecimovic (2023), who found that AI adoption in auditing is influenced by technological, organizational, and environmental factors, including data quality, organizational readiness, trust, regulation, and perceived control. Their concern regarding the limited control associated with AI “black-box” systems reinforces the present finding that explainability and human oversight are necessary for maintaining professional accountability (Seethamraju & Hecimovic, 2023).

Eighth, the findings also correspond with Ntoutsis et al. (2020), who demonstrate that algorithmic bias can originate from data, model development, and broader socio technical structures and therefore cannot be solved exclusively through technical adjustments. The present review extends this argument into auditing by proposing that

bias identification should be connected with accountability, explainability, and human professional judgment throughout the AI audit lifecycle (Ntoutsis et al., 2020).

Taken together, the comparison of eight prior studies indicates that existing research has generally examined AI performance, ethical risks, bias, explainability, or governance separately, whereas this SLR integrates these dimensions into a unified trustworthy-auditing perspective (Murikah et al., 2024; Fedyk et al., 2022; Lehner et al., 2022). The principal theoretical implication is therefore that trustworthy AI auditing should be conceptualized as a socio-technical governance system in which algorithmic fairness, ethical accountability, explainability, and human oversight mutually reinforce one another (Mökander & Floridi, 2021; McDermid et al., 2021).

CONCLUSION

This qualitative systematic literature review concludes that the development of trustworthy auditing in the era of artificial intelligence requires more than technological accuracy and automation. The synthesis identifies four interconnected dimensions: algorithmic bias and fairness, AI ethics and accountability, explainability and transparency, and human oversight and professional judgment as fundamental elements for responsible AI-enabled auditing. The findings indicate that algorithmic bias may originate from data, model design, and broader socio-technical conditions, making continuous monitoring and fairness-oriented evaluation necessary. AI ethics and accountability are equally important because responsibility for AI supported audit decisions extends beyond system developers to auditors, organizations, and governance structures. Explainability provides auditors with the ability to understand, challenge, document, and justify AI-generated outputs, while human oversight ensures that professional judgment remains central to consequential audit decisions. Overall, the review supports a shift from viewing AI primarily as an efficiency-enhancing technology toward understanding AI-enabled auditing as a socio-technical governance process that combines technological capability with ethical responsibility, transparency, accountability, and human judgment.

LIMITATION

Several limitations should be acknowledged. First, as a qualitative systematic literature review, the findings depend on the scope, quality, and methodological characteristics of the studies available in the selected literature. Second, the interdisciplinary nature of AI auditing research creates differences in terminology and conceptual definitions across accounting, auditing, computer science, information systems, and ethics, which may affect the comparability of findings. Third, the synthesis is interpretive rather than statistically aggregated and therefore does not estimate quantitative effect sizes. Future research should conduct longitudinal empirical studies and develop validated frameworks for measuring bias, explainability, accountability, and human oversight in real world AI enabled auditing environments.

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