

Artificial intelligence and auditing: Legal and ethical implications for assurance providers

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Abstract

Artificial intelligence (AI) is changing audit practice by expanding analytical coverage, automating routine procedures, and supporting more continuous risk assessment. These benefits, however, also raise questions about accountability, explainability, professional judgment, data protection, and legal responsibility. This study examines whether AI auditability and oversight design shape assurance professionals' perceptions of ethical risk, legal exposure, and audit quality in Ghana. Using a quantitative design, the study combines a cross-sectional survey of 180 assurance professionals with a between-subjects vignette experiment. AI auditability was assessed in terms of data traceability, model documentation, explainability, governance controls, role clarity, and human-in-the-loop (HITL) procedures. The experiment compared manual-only auditing, AI-only auditing, and AI-assisted auditing with HITL oversight. AI auditability was negatively associated with perceived ethical risk ($\beta = -0.456$, $p < .001$) and positively associated with perceived audit quality ($\beta = 0.424$, $p < .001$). Perceived ethical risk was positively associated with perceived legal exposure ($\beta = 0.536$, $p < .001$) and negatively associated with perceived audit quality ($\beta = -0.268$, $p < .001$). Although AI auditability was negatively correlated with perceived legal exposure, its direct regression effect was not statistically significant after ethical risk was controlled ($\beta = -0.092$, $p = .392$). The experiment showed that AI-only oversight was associated with higher perceptions of ethical and legal risk than AI-assisted auditing with HITL oversight. Because the study measures professional perceptions rather than observed legal events or realized audit outcomes, the findings should be interpreted as evidence about perceived risk and quality. Overall, the results indicate that responsible AI adoption in auditing depends less on automation alone than on auditable governance, meaningful human oversight, and clear accountability.

Keywords: Artificial Intelligence Auditing, AI Auditability, Legal Exposure, Ethical Risk, Audit Quality, Human-In-The-Loop Oversight

JEL Classification: M42, O33, O55, K20

1. Introduction

Artificial intelligence (AI) is changing the way assurance work is planned, performed, and reviewed. AI-enabled tools can process large volumes of structured and unstructured information, identify unusual transactions, support risk assessment, and automate repetitive procedures. These capabilities can broaden analytical coverage and improve the timeliness of audit work. At the same time, they create a different set of professional questions: who is accountable when an AI-supported judgment is wrong, how can an auditor explain an opaque output, and what evidence is sufficient to demonstrate that the technology was appropriately governed? (Munoko et al., 2020; Li & Goel, 2025).

The governance question has therefore become more important than the automation question. International frameworks increasingly emphasize transparency, accountability, documentation, risk management, and human oversight. The European Union Artificial Intelligence Act provides a risk-based governance framework, while the NIST AI Risk Management Framework offers lifecycle-oriented guidance for identifying and managing AI risks. The OECD AI Principles similarly emphasize transparency, accountability, fairness, safety, and human-centered governance (European Union, 2024; NIST, 2023; OECD, 2024). Rather than treating these frameworks separately, this study uses their common governance themes to motivate a single argument: AI can be useful in assurance only when its operation and outputs remain sufficiently understandable, traceable, reviewable, and accountable.

The literature on AI-assisted auditing reflects this tension. AI may improve anomaly detection and analytical coverage, but excessive reliance on automated outputs can weaken professional skepticism and make responsibility less clear. Opacity can also make it difficult to determine why a system produced a particular recommendation, while biased or incomplete training data may affect audit judgments (Munoko, Brown-Liburd, & Vasarhelyi, 2020). These concerns are not merely technical. They can affect ethical judgments, perceptions of legal vulnerability, and confidence in the quality of an assurance engagement.

AI auditability provides a useful way to connect these concerns. In this study, AI auditability refers to the extent to which AI systems and their outputs can be traced, documented, explained, reviewed, and evaluated. Relevant governance artifacts include data lineage, model documentation, explainability mechanisms, lifecycle controls, defined responsibilities, and documented human review (Li & Goel, 2025). Human-in-the-loop (HITL) oversight is especially important because it preserves the auditor's authority to question, challenge, and override AI-generated outputs rather than treating the technology as an autonomous decision-maker (Schiff, Kelley, & Camacho, 2024).

The Ghanaian context makes this issue particularly relevant. AI-enabled audit analytics are beginning to receive attention within Ghana's assurance environment, while the Data Protection Act 843 and Cybersecurity Act 1038 establish obligations concerning lawful data processing,

privacy, cybersecurity, and accountability (Republic of Ghana, 2012; 2020). Professional developments have also increased the need for auditors to strengthen technological competence and digital-assurance skills. Yet empirical evidence on how assurance professionals in Ghana perceive the ethical, legal, and audit-quality implications of AI governance remains limited.

Three gaps motivate the study. First, much of the existing evidence is conceptual or drawn from developed economies, leaving African and other Global South contexts comparatively underrepresented. Second, relatively few studies connect specific AI governance mechanisms—such as traceability, documentation, explainability, and human oversight—to auditors’ perceptions of ethical risk, legal exposure, and audit quality. Third, less attention has been paid to oversight design, particularly the difference between AI-only workflows and AI-assisted workflows in which human professionals retain review and override authority.

This study addresses these gaps by examining how AI auditability and oversight design are associated with perceived ethical risk, perceived legal exposure, and perceived audit quality among assurance professionals in Ghana. It combines survey evidence on naturally occurring professional perceptions with a vignette experiment that compares manual-only auditing, AI-only auditing, and AI-assisted auditing with HITL oversight. The study is guided by Risk Governance Theory and Socio-Technical Systems Theory, which together suggest that risk and performance are shaped by both governance arrangements and the interaction between technological systems and human actors. The study makes two main contributions. First, it extends emerging research on AI auditability and responsible AI governance by providing empirical evidence from the Ghanaian assurance environment. Second, it shows why the design of oversight matters: the relevant question is not simply whether AI is used, but whether its use is supported by governance mechanisms that preserve transparency, accountability, and professional judgment.

Based on the theoretical arguments and prior empirical evidence, the study tests the following hypotheses:

H1: Higher levels of AI auditability are associated with lower perceived ethical risk among assurance professionals.

H2: Higher levels of AI auditability are associated with higher perceived audit quality.

H3: Higher perceived ethical risk is associated with higher perceived legal exposure.

H4: Higher perceived ethical risk is associated with lower perceived audit quality.

H5: Compared with manual-only auditing, AI-only auditing generates higher perceptions of ethical and legal risk.

H6: Compared with AI-only auditing, AI-assisted auditing with HITL oversight generates lower perceptions of ethical and legal risk.

2. Literature Review

2.1 Artificial Intelligence and the Transformation of Auditing

Artificial intelligence (AI) is increasingly transforming the auditing profession by enhancing the speed, scope, and efficiency of audit procedures. AI-enabled systems allow auditors to analyze entire populations of transactions, identify anomalies in real time, automate repetitive tasks, and improve the quality of evidence gathering through advanced analytics and machine learning techniques (Munoko et al., 2020; Li & Goel, 2025). Unlike traditional audit approaches that rely heavily on sampling and manual testing, AI-assisted auditing enables continuous monitoring and predictive analysis, thereby expanding the auditor's ability to detect irregularities and emerging risks. Recent developments in data analytics, natural language processing, and machine learning have encouraged audit firms to integrate AI tools into areas such as fraud detection, risk assessment, journal-entry testing, and internal-control evaluation. Large international accounting firms increasingly employ AI-driven platforms to improve audit efficiency and decision-making quality (Munoko et al., 2020; Li & Goel, 2025). These technologies are capable of processing structured and unstructured datasets at a scale beyond human capability, thereby improving the timeliness and comprehensiveness of assurance engagements.

Despite these advantages, the growing reliance on AI systems has generated significant concerns regarding professional judgment, accountability, transparency, and ethical responsibility. Scholars argue that excessive dependence on automated systems may weaken professional skepticism and reduce auditors' ability to critically challenge audit evidence (Munoko, Brown-Liburd, & Vasarhelyi, 2020). Furthermore, AI systems may produce outcomes that are difficult to interpret due to the "black-box" nature of certain machine learning models, thereby complicating the auditor's responsibility to explain and justify audit conclusions. Consequently, the adoption of AI in auditing has shifted professional attention from technological capability alone to broader questions of governance, explainability, and human oversight. International regulatory frameworks increasingly reflect this shift. The European Union Artificial Intelligence Act establishes a risk-based approach to AI governance by emphasizing transparency, human oversight, documentation, and accountability in high-impact AI applications (European Union, 2024). Similarly, the U.S. National Institute of Standards and Technology (NIST) AI Risk Management Framework provides guidance for identifying and mitigating AI-related risks across the lifecycle of AI systems (NIST, 2023). The OECD AI Principles further reinforce the need for fairness, accountability, transparency, and respect for human rights in AI deployment (OECD, 2024). Together, these frameworks suggest that AI systems used in auditing must not only be efficient but also auditable, explainable, and ethically governed.

2.2 Ethical Risks Associated with AI-Assisted Auditing

The increasing use of AI in auditing has intensified concerns regarding ethical risk within assurance engagements. Ethical risk in AI-assisted auditing refers to the possibility that AI systems

may generate unfair, biased, opaque, or harmful outcomes that undermine professional integrity, stakeholder trust, and public confidence in audit processes.

One major concern relates to algorithmic bias. AI systems learn from historical datasets, and where those datasets contain inaccuracies, omissions, or embedded social biases, the resulting outputs may reproduce or amplify discriminatory patterns. In auditing, biased AI systems may distort risk assessments, anomaly detection, or client evaluations, thereby affecting audit judgments and conclusions. Researchers argue that the lack of transparency in machine-learning models further complicates the detection and correction of such biases (Murikah, Nthenge, & Musyoka, 2024).

Another ethical concern involves accountability and explainability. Many advanced AI systems operate as opaque “black boxes,” making it difficult for auditors, regulators, or stakeholders to understand how conclusions were generated. This opacity creates what scholars describe as a “responsibility gap,” where responsibility for erroneous or harmful outcomes becomes unclear (Munoko et al., 2020). In professional auditing environments, such ambiguity threatens the auditor’s obligation to exercise due care, maintain professional skepticism, and provide defensible assurance conclusions. Privacy and data-security concerns also represent important ethical challenges (Munoko et al., 2020; Murikah et al., 2024; OECD, 2024). AI systems often require access to large volumes of sensitive client information during training, testing, and operational deployment. Improper handling of such data may expose firms to confidentiality breaches, unauthorized access, and misuse of personal or corporate information. Consequently, ethical AI governance requires strong safeguards relating to lawful data processing, cybersecurity, and confidentiality protection. To address these concerns, scholars increasingly emphasize the importance of governance mechanisms such as representative testing, explainability tools, human oversight, and documented review procedures. Human-in-the-loop (HITL) oversight, in particular, has emerged as a critical ethical safeguard because it ensures that human professionals retain authority to review, challenge, and override AI-generated outputs where necessary (Schiff, Kelley, & Camacho, 2024; Langer et al., 2024). This suggests that ethical risk in AI-assisted auditing depends not merely on whether AI is used, but on how AI systems are governed and supervised within audit engagements.

2.3 AI Auditability and Governance Mechanisms

The concept of AI auditability has become increasingly important within discussions of responsible AI governance. AI auditability refers to the extent to which AI systems can be examined, traced, documented, explained, and independently evaluated by auditors and other stakeholders. In auditing contexts, auditability provides the foundation for assessing whether AI-generated outputs are reliable, transparent, and consistent with professional and regulatory expectations.

Li and Goel (2025) argue that credible assurance over AI systems requires the existence of several governance artifacts, including traceable data lineage, model documentation, lifecycle controls,

explainability mechanisms, and clearly assigned responsibilities. Data lineage refers to the ability to trace the origin, movement, and transformation of data used by AI systems. Model documentation, including model cards and system descriptions, helps explain the purpose, limitations, assumptions, and operational boundaries of AI models. Explainability tools provide insight into how AI systems generate outputs, thereby improving transparency and interpretability.

Human oversight mechanisms are equally important components of AI auditability. Human-in-the-loop (HITL) frameworks ensure that auditors retain authority over AI-assisted decisions by reviewing outputs, exercising professional judgment, and documenting override actions where necessary. Such controls are critical because they preserve accountability and reduce excessive reliance on automated systems.

Existing research suggests that stronger auditability mechanisms improve trust in AI-assisted auditing by increasing transparency and reducing uncertainty (Li & Goel, 2025; Schiff et al., 2024). However, empirical evidence linking AI auditability directly to perceived ethical risk, legal exposure, and audit quality remains limited, particularly in developing-country contexts. Most existing studies are conceptual or focused on advanced economies, leaving a significant gap regarding how auditors in emerging markets perceive and evaluate AI governance controls in practice.

2.4 Legal Exposure and Regulatory Accountability

The adoption of AI in auditing also raises important legal and regulatory concerns. Legal exposure refers to the perceived likelihood of litigation, regulatory sanctions, financial penalties, or reputational damage arising from the use of AI systems within assurance engagements (Libby & Witz, 2024; Farley & Lansang, 2025). As AI systems increasingly influence audit judgments and evidence evaluation, questions emerge regarding liability for errors, bias, negligence, or inadequate oversight.

Behavioral legal research suggests that perceptions of liability are closely linked to transparency and governance quality. Libby and Witz (2024) found that AI-assisted decision-making may reduce negligence judgments where AI use is transparent, properly documented, and supported by rigorous oversight procedures. Conversely, poorly governed AI systems may increase perceptions of legal vulnerability, especially where decision processes are opaque or inadequately supervised.

The legal implications of AI-assisted auditing are further reinforced by emerging regulatory frameworks. The European Union AI Act requires organizations deploying high-risk AI systems to maintain documentation, human oversight, risk-management controls, and transparency obligations (European Union, 2024). Similarly, the NIST AI RMF emphasizes accountability, traceability, and governance as essential mechanisms for reducing AI-related legal and operational risks (NIST, 2023).

Within Ghana, the Data Protection Act 843 and the Cybersecurity Act 1038 establish legal obligations relating to data privacy, cybersecurity, lawful processing, and accountability (Republic of Ghana, 2012; 2020). These laws become particularly relevant where AI systems process sensitive client information during audit engagements. Assurance providers that fail to implement adequate governance controls may therefore face increased regulatory scrutiny and legal exposure. Although legal and ethical concerns surrounding AI have received growing scholarly attention, relatively few studies empirically examine how specific governance arrangements, particularly oversight design and auditability mechanisms, shape auditors' perceptions of legal risk. This gap is especially evident within African and developing-country contexts, where empirical evidence remains scarce.

2.5 AI, Professional Judgment, and Audit Quality

Audit quality remains a central concern in discussions surrounding AI-assisted assurance. Audit quality generally refers to the extent to which audit procedures produce reliable, sufficient, objective, and professionally defensible audit evidence (DeAngelo, 1981; Francis, 2011; International Auditing and Assurance Standard Board, 2024). Proponents of AI argue that AI-assisted auditing can improve audit quality by increasing analytical coverage, reducing human error, enhancing anomaly detection, and improving the consistency of audit procedures.

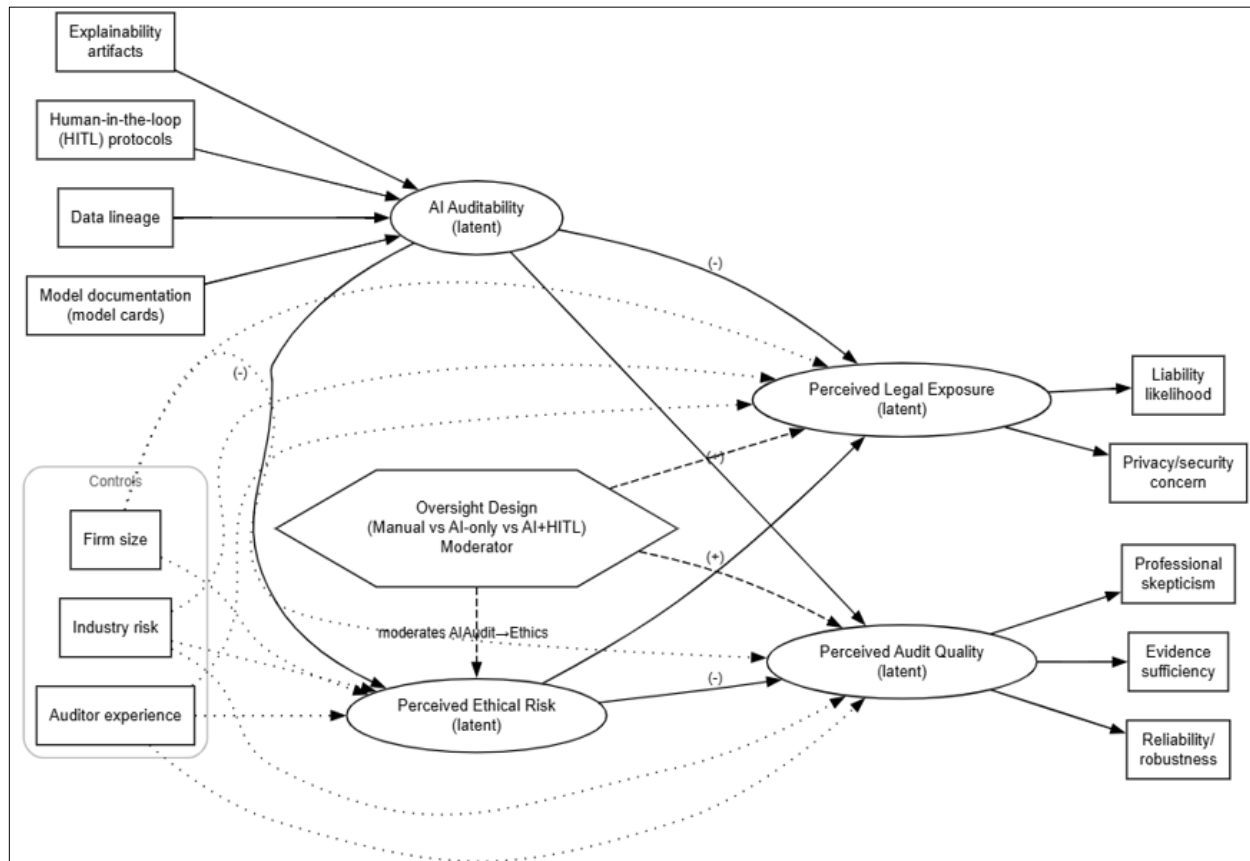
However, scholars caution that AI adoption may also introduce new risks capable of undermining audit quality. Overreliance on automated systems may weaken professional skepticism, reduce critical thinking, and encourage excessive trust in algorithmic outputs (Munoko et al., 2020; International Ethics Standards Board for Accountants, 2024). Where AI-generated conclusions are not adequately reviewed or challenged, audit quality may deteriorate despite technological sophistication.

Existing literature increasingly suggests that the relationship between AI and audit quality depends heavily on governance quality. Strong auditability controls, explainability mechanisms, and structured human oversight may enhance audit quality by improving transparency, reproducibility, and accountability. In contrast, AI-only workflows that lack meaningful human review may increase uncertainty and reduce confidence in audit conclusions.

Empirical evidence regarding these relationships remains limited, particularly in developing economies. Few studies directly examine how AI auditability and ethical risk perceptions influence perceived audit quality among practicing auditors. This study addresses that gap by empirically investigating how governance mechanisms shape auditors' perceptions of quality within AI-assisted assurance engagements.

Figure 1 presents the conceptual framework of AI auditability, legal exposure, ethical risk, and audit quality. It presents the pictorial view of the research variables.

Figure 1. Conceptual Frame of AI Auditability, Legal Exposure, Ethical Risk and Audit Quality



3. Methodology

3.1 Research Design

This study adopted an explanatory cross-sectional research design combined with a between-subjects vignette experiment to examine how AI auditability and oversight design influence perceived ethical risk, perceived legal exposure, and perceived audit quality among assurance professionals in Ghana. The explanatory design was appropriate because the study sought to test theoretically grounded relationships among governance-related variables within AI-assisted auditing environments. The cross-sectional survey component enabled the collection of data from practicing auditors and assurance professionals at a single point in time regarding their perceptions, experiences, and governance practices relating to AI-assisted auditing. In addition, the vignette experiment was incorporated to strengthen causal inference by examining how different oversight conditions influence respondents' ethical- and legal-risk perceptions under controlled scenarios. The study integrated both observational and experimental elements to provide a more comprehensive understanding of AI governance in auditing. While the survey component

examined naturally occurring relationships among constructs, the vignette experiment isolated the effect of oversight design by randomly assigning respondents to different audit scenarios.

3.2 Research Approach

The study employed a quantitative research approach because the research objectives required the measurement and statistical analysis of relationships among latent governance and risk constructs. Quantitative methods were appropriate for testing hypotheses, estimating structural relationships, and comparing differences across experimental conditions. The research design was guided by risk-governance theory and socio-technical systems theory. Risk-governance theory suggests that transparency, accountability, and traceability mechanisms reduce perceived uncertainty and risk within organizational systems (Renn, 2008). Socio-technical systems theory emphasizes the interdependence between technological systems and human oversight structures (Baxter & Sommerville, 2011). Together, these theories support the argument that AI governance mechanisms and human oversight influence ethical risk, legal exposure, and perceived audit quality within AI-assisted auditing environments.

3.3 Population of the Study

The target population consisted of assurance professionals involved in financial-statement auditing and related assurance services within Ghana. The population included audit partners, audit managers, senior auditors, audit associates, internal auditors, IT audit specialists, and data analytics professionals working within audit firms. Participants were drawn from Big Four audit firms, large local firms, medium-sized practices, and smaller indigenous audit firms. The inclusion of professionals from different organizational sizes and functional roles enhanced the diversity and representativeness of the sample regarding AI adoption and governance practices within the Ghanaian assurance environment.

3.4 Sampling Technique and Sample Size

Purposive sampling with quota-based stratification was used to obtain coverage across firm types and professional roles. The quotas were intended to prevent the sample from being dominated by a single organizational category, while purposive selection ensured that participants had relevant assurance experience. Recruitment was conducted electronically through professional accounting networks, Institute of Chartered Accountants, Ghana (ICAG) professional groups, LinkedIn searches, audit training forums, university alumni networks, and practitioner WhatsApp and Telegram groups. Convenience and referral recruitment were used as supplementary access routes. These procedures were appropriate given the absence of a comprehensive national sampling frame of assurance professionals with AI experience, but they also mean that the sample should not be treated as a probability sample of all Ghanaian auditors.

A total of 240 questionnaires were distributed electronically, of which 180 usable responses were retained after screening for completeness and response validity. The vignette experiment randomly

assigned respondents to the three oversight conditions. The final groups comprised 57 respondents in the AI-assisted + HITL condition, 63 in the AI-only condition, and 60 in the manual-only condition. The relatively balanced allocation supports comparison across conditions, although the non-probability recruitment limits statistical generalizability beyond the sampled professionals.

3.5 Data Collection Instrument

Data were collected through a structured, self-administered online questionnaire. The instrument contained survey measures of AI auditability (AUDITAB), perceived ethical risk (ETHRISK), perceived legal exposure (LEGALEX), and perceived audit quality (AUDQUAL), using seven-point Likert scales from 1 = Strongly Disagree to 7 = Strongly Agree. AI auditability covered data-lineage traceability, model documentation, explainability mechanisms, governance controls, role clarity, and HITL procedures. Ethical risk covered bias and fairness, transparency limitations, privacy, and accountability. Legal exposure covered perceived litigation risk, regulatory vulnerability, compliance exposure, and reputational liability. Audit quality covered perceived evidence sufficiency, reliability of procedures, robustness of judgments, and maintenance of professional skepticism.

The vignette was embedded in the same online administration and was randomly assigned between subjects. Each participant read one audit scenario involving anomaly detection and evidence evaluation. The substantive audit context was held constant while the oversight arrangement varied across the three conditions: manual-only, AI-only, or AI-assisted with HITL oversight. After reading the scenario, respondents rated perceived ethical risk and perceived legal exposure using the vignette measures V1 and V2. Manipulation-check items were included to assess whether respondents recognized the oversight arrangement to which they had been assigned.

3.6 Validity and Reliability of the Instrument

To ensure content validity, the questionnaire was reviewed by accounting academics, AI governance researchers, and senior audit practitioners. Feedback from these experts was used to refine item wording, construct clarity, and contextual relevance. A pilot study involving practicing auditors was conducted prior to the main survey. Ambiguous or repetitive items were revised or removed based on pilot feedback. Reliability was assessed using Cronbach's alpha coefficients. These procedures ensured that the measurement items adequately represented their intended constructs.

Table 1. Reliability and Validity Assessment

Construct	Items	Cronbach Alpha	Composite Reliability	AVE	VIF
AI Auditability	19	0.986	0.987	0.801	5.79

Construct	Items	Cronbach Alpha	Composite Reliability	AVE	VIF
Ethical Risk	9	0.964	0.969	0.777	1.76
Legal Exposure	9	0.973	0.977	0.824	3.73
Audit Quality	9	0.967	0.972	0.793	1.63

All Cronbach's alpha values for all principal constructs in Table 1 exceed the recommended threshold of 0.70, indicating satisfactory internal consistency. This suggests that the items used to measure AI auditability, perceived ethical risk, perceived legal exposure, and perceived audit quality were sufficiently reliable for statistical analysis. The strongest reliability scores were observed for AI auditability and perceived ethical risk, indicating relatively stable responses across governance-related items such as explainability, documentation, traceability, and oversight controls. Construct validity was evaluated using average variance extracted (AVE), and discriminant validity assessments as indicated in Table 1. The results in Table 1 showed that the measurement items loaded strongly onto their intended constructs, supporting convergent validity. In addition, discriminant validity tests indicated that the constructs were empirically distinct from one another. This finding was important because ethical risk, legal exposure, and audit quality are conceptually related but analytically separate dimensions of AI governance in auditing. Collectively, these results support the adequacy of the measurement model and provide confidence for subsequent structural analysis. Also, all the VIF values in Table 1 are less than 10. The measurement scales are therefore considered highly reliable for assessing AI governance, ethical risk, legal exposure, and audit quality.

3.7 Variable Measurement

The study operationalized four principal constructs: AI auditability (AUDITAB), perceived ethical risk (ETHRISK), perceived legal exposure (LEGALEX), and perceived audit quality (AUDQUAL). Oversight design was treated as a three-level experimental factor: manual-only, AI-only, and AI-assisted + HITL. Dummy variables were created for regression analysis, with manual-only as the reference category. Control variables included years of experience, prior AI use, firm size, professional role, and governance posture. The survey constructs and the vignette outcomes were treated as distinct measures; the latter are identified as V1 (ethical risk) and V2 (legal exposure) in the experimental analyses.

3.8 Model Specification

The study estimated multivariate three regression models corresponding to the research objectives.

Model 1: Ethical Risk Model

Perceived ethical risk was modeled as:

$$\text{ETHRISK}_i = \alpha_0 + \alpha_1 \cdot \text{AUDITAB}_i + \alpha_2 \cdot \text{Aionly}_i + \alpha_3 \cdot \text{AIHITL}_i + \alpha_4 \cdot (\text{AUDITAB}_i \times \text{Aionly}_i) + \alpha_5 \cdot (\text{AUDITAB}_i \times \text{AIHITL}_i) + \alpha_c \cdot X_i + \varepsilon_{1i}.$$

This model examined the effect of AI auditability on ethical risk, and the moderating effect of oversight design.

Model 2: Legal Exposure Model

$$\text{LEGALEX}_i = \beta_0 + \beta_1 \cdot \text{ETHRISK}_i + \beta_2 \cdot \text{AUDITAB}_i + \beta_3 \cdot \text{Aionly}_i + \beta_4 \cdot \text{AIHITL}_i + \beta_c \cdot X_i + \varepsilon_{2i}.$$

This model examined the relationship between ethical risk and legal exposure, the direct effect of auditability, and the influence of oversight design.

Model 3: Audit Quality Model

$$\text{AUDQUAL}_i = \gamma_0 + \gamma_1 \cdot \text{AUDITAB}_i + \gamma_2 \cdot \text{ETHRISK}_i + \gamma_c \cdot X_i + \varepsilon_{3i}.$$

This model examined the effect of AI auditability on perceived audit quality, and the influence of ethical risk on quality perceptions.

3.9 Data Analysis Techniques

The survey data were analyzed using descriptive statistics, reliability analysis, correlation analysis, robust ordinary least squares (OLS) regression, and variance-inflation-factor diagnostics. HC3 heteroskedasticity-consistent standard errors were used for regression inference. The vignette data were analyzed using one-way ANOVA, Welch tests, and planned/post-hoc contrasts. Additional checks included centered interaction specifications, sensitivity analysis, bootstrap confidence intervals, and alternative contrast coding. The results reported below focus on the estimates available in the supplied manuscript.

The vignette experiment was analyzed using one-way ANOVA, Welch tests, and planned contrasts to compare differences across oversight conditions. Additional robustness checks included variance inflation factor (VIF) analysis, centered interaction specifications, sensitivity analysis, bootstrap confidence intervals, and alternative contrast coding procedures.

3.10 Ethical Considerations

Participation was voluntary, and respondents were informed about the study before completing the online questionnaire. Confidentiality and anonymity were maintained, no personally identifiable information was reported, and participants could discontinue participation without penalty. The supplied manuscript does not identify the institutional ethics committee, approval number, or formal exemption decision. To satisfy reporting requirements, the final version should state the applicable ethics approval or exemption explicitly (e.g., approving institution and reference number, where applicable). No such information is inferred here.

Confidentiality and anonymity were maintained throughout the research process. No personally identifiable information was disclosed in the analysis or reporting of findings. Respondents were also informed that participation could be discontinued at any stage without penalty. Data collected through the online survey platform were securely stored and used strictly for academic purposes.

4. Results and Discussion

This section presents the empirical findings of the study and discusses their implications in relation to the research objectives and existing literature. The analysis focuses on how AI auditability and oversight design influence perceived ethical risk, perceived legal exposure, and perceived audit quality among assurance professionals in Ghana. It is organized into four sections. First, descriptive statistics and respondent characteristics are presented. Second, the reliability and validity of the measurement model are examined. Third, the structural and experimental results are reported. Finally, the findings are discussed in relation to prior studies, AI governance frameworks, and auditing practice.

4.1 Respondent Characteristics

A total of 180 usable responses were included in the final analysis. Respondents represented a broad cross-section of assurance professionals across Ghana's auditing industry, including professionals from Big Four firms, large local firms, medium-sized practices, and smaller indigenous firms.

Most respondents had practical experience in financial-statement auditing, internal audit, IT assurance, or data analytics. The sample included audit associates, senior auditors, managers, partners, and internal-control specialists. This diversity improved the relevance of the findings because perceptions regarding AI governance may differ across levels of professional responsibility and technological exposure.

The majority of respondents reported at least moderate familiarity with AI-assisted audit tools, including data analytics platforms, anomaly-detection systems, and automated risk-assessment applications. However, levels of direct operational use varied considerably across firms, suggesting that AI adoption within Ghana's auditing environment remains uneven and still evolving. In all, the respondent profile supports the study's objective of examining professional perceptions regarding AI governance and oversight within practical assurance settings.

4.2 Descriptive Statistics and Correlation Analysis

Table 2 separates the survey-based construct measures from the vignette-specific outcome measures. AUDITAB, ETHRISK, LEGALEXP, and AUDQUAL are the survey constructs, whereas V1 and V2 are the ethical-risk and legal-exposure measures collected after exposure to the vignette.

Table 2. Survey Construct and Vignette Outcome Means by Oversight Condition

Condition	Survey Auditability Mean (SD)	AI Survey Ethical Risk Mean (SD)	Survey Legal Exposure Mean (SD)	Survey Audit Quality Mean (SD)	Vignette Ethics Risk (V1) Mean (SD)	Vignette Legal Exposure (V2) Mean (SD)	n
AI +HITL	5.25 (0.82)	4.01 (0.61)	4.81 (0.75)	5.92 (0.66)	3.63 (0.59)	4.86 (0.79)	5
AI-only	5.30 (0.74)	4.83 (0.53)	6.12 (0.50)	5.77 (0.65)	5.41 (0.53)	6.06 (0.54)	6
Manual	5.39 (0.78)	4.29 (0.58)	5.37 (0.61)	6.00 (0.70)	4.43 (0.56)	5.43 (0.65)	6

The vignette measures show a clear pattern across oversight conditions. The AI-only condition has the highest mean perceived ethical risk (V1 = 5.41) and legal exposure (V2 = 6.06), while the AI-assisted + HITL condition has the lowest values (V1 = 3.63; V2 = 4.86). The manual-only condition falls between the two. These descriptive differences are consistent with the inferential tests reported below.

The survey-based audit-quality means are relatively high across the three groups, but the ANOVA reported below does not indicate a statistically significant difference in perceived audit quality across conditions. It is therefore more appropriate to describe the means as broadly similar rather than to conclude that one condition is demonstrably superior on audit quality.

Overall, the descriptive results suggest that respondents distinguish between the use of AI and the governance arrangement surrounding that use. In particular, the vignette results indicate greater concern when AI operates without stated human oversight and lower concern when human review and override authority are explicitly retained.

In all, the descriptive statistics in Table 2 reveal that assurance professionals are generally receptive to AI adoption but remain cautious about fully autonomous AI systems. Their perceptions emphasize that governance quality, rather than AI technology itself, largely determines confidence in AI-assisted auditing. These preliminary observations provide an important foundation for the subsequent regression analyses, which formally examine the relationships among AI auditability, ethical risk, legal exposure, and audit quality.

4.3. Correlation Matrix

Table 3. Correlation Analysis of AI Auditability, Ethical Risk, Legal and Audit Quality

Variable	Mean	SD	1	2	3	4
AI Auditability	5.3	0.74	1			
Ethical Risk	4.83	0.53	-0.637***	1		
Legal Exposure	6.12	0.50	-0.528***	0.829***	1	
Audit Quality	5.77	0.65	0.802***	-0.673***	-0.557***	1

The correlation matrix in Table 3 indicates that AI auditability is negatively associated with perceived ethical risk ($r = -0.637$, $p < .001$) and perceived legal exposure ($r = -0.528$, $p < .001$), and positively associated with perceived audit quality ($r = 0.802$, $p < .001$). Perceived ethical risk is positively associated with perceived legal exposure ($r = 0.829$, $p < .001$) and negatively associated with perceived audit quality ($r = -0.673$, $p < .001$). Perceived legal exposure is also negatively associated with perceived audit quality ($r = -0.557$, $p < .001$).

Table 4 presents the comparison of oversight conditions of ethical risk, legal exposure, and audit quality.

Table 4. One-Way ANOVA Comparing Oversight Conditions

Outcome	F	Df	p-value	Decision
Ethical Risk (V1)	153.16	(2,177)	<0.001	Significant
Legal Exposure (V2)	49.77	(2,177)	<0.001	Significant
Audit Quality	1.83	(2,177)	=0.164	Not Significant

Oversight design significantly influenced both perceived ethical risk and perceived legal exposure. Ethical risk differed across conditions, $F(2, 177) = 153.16$, $p < .001$, and legal exposure also differed significantly, $F(2, 177) = 49.77$, $p < .001$. The difference in perceived audit quality across conditions was not statistically significant, $F(2, 177) = 1.83$, $p = .164$. Thus, the experimental evidence is strongest for risk perceptions, not for differences in perceived audit quality.

Table 5. Post-hoc Comparisons of Ethical Risk, and Legal Exposure

Comparison	Mean Difference	Hedges' g	p-value
AI-only vs Manual	0.98	1.784	<0.001
AI+HITL vs AI-only	-1.78	-3.181	<0.001
AI-only vs Manual	0.63	1.057	<0.001
AI+HITL vs AI-only	-1.20	-1.791	<0.001

The post-hoc comparisons show that AI-only auditing produced substantially higher vignette ethical-risk perceptions than manual-only auditing (mean difference = 0.98, Hedges' $g = 1.784$, $p < .001$), while AI-assisted + HITL produced substantially lower ethical-risk perceptions than AI-only auditing (mean difference = -1.78 , Hedges' $g = -3.181$, $p < .001$). For legal exposure, AI-only was higher than manual-only (mean difference = 0.63, Hedges' $g = 1.057$, $p < .001$), whereas AI-assisted + HITL was lower than AI-only (mean difference = -1.20 , Hedges' $g = -1.791$, $p < .001$). The table should identify the outcome for each comparison explicitly.

4.4 Regression Results

4.4.1 AI Auditability and Perceived Ethical Risk

Table 6 presents Model 1, which examines perceived ethical risk. AI auditability has a statistically significant negative association with perceived ethical risk ($\beta = -0.4562$, $p < .001$). The interaction terms between auditability and the oversight conditions are not statistically significant. The result supports H1: respondents who perceive stronger auditability also tend to report lower ethical-risk perceptions.

Table 6. Model 1. Predictors of Perceived Ethical Risk (ETHRISK)

Variable	Coefficient	HC3 SE	T	P
Intercept	6.8143	0.4026	16.9276	<0.001
AUDITAB	-0.4562	0.0982	-4.6444	<0.001
AI-only	0.6285	0.5387	1.1668	0.243
AI+HITL	0.0706	0.4966	0.1422	0.887

Variable	Coefficient	HC3 SE	T	P
AUDITAB × AI-only	−0.0271	0.1017	−0.2663	0.790
AUDITAB × AI+HITL	−0.0815	0.0955	−0.8531	0.394

The finding is consistent with a governance interpretation of AI risk. Traceable audit trails, explainability, documentation, defined responsibilities, and structured review procedures can make AI-supported work easier to understand and challenge. Importantly, the interaction results do not show that the auditability–ethical-risk association varies significantly across the three oversight conditions. The main effect of auditability should therefore be emphasized, while claims about moderation should be avoided.

The result also fits the combined theoretical framework. Risk Governance Theory predicts that transparency and accountability mechanisms can reduce perceived uncertainty (Renn, 2008), while Socio-Technical Systems Theory suggests that technology is embedded in organizational roles and controls (Baxter & Sommerville, 2011). The practical implication is not that AI is inherently low-risk, but that auditable governance can reduce professionals’ concerns about its use.

4.4.2 AI Auditability and Perceived Audit Quality

Table 7 presents Model 2, which examines perceived audit quality. AI auditability is positively associated with perceived audit quality ($\beta = 0.4240$, $p < .001$), while perceived ethical risk is negatively associated with perceived audit quality ($\beta = -0.2677$, $p < .001$). These results support H2 and H4.

Table 7. Model 2. Predictors of Perceived Audit Quality (AUDQUAL)

Variable	Coefficient	HC3 SE	T	P
Intercept	4.4323	0.5208	8.5106	<0.001
AUDITAB	0.4240	0.0907	4.6734	<0.001
ETHRISK	−0.2677	0.0588	−4.5502	<0.001
Prior AI Use	0.0865	0.0430	2.0142	0.044

The results suggest that auditors associate stronger auditability with greater confidence in the reliability and defensibility of AI-supported audit work. At the same time, ethical concerns appear to undermine those quality perceptions. The interpretation should remain perceptual: the analysis

does not establish that auditability improves objective audit quality, reduces actual audit errors, or changes the quality of completed engagements.

Prior AI use is also positively associated with perceived audit quality ($\beta = 0.0865$, $p = .044$). This may indicate that practical familiarity with AI is associated with greater confidence in its potential contribution to assurance work. However, the cross-sectional design does not establish whether AI experience causes more favorable perceptions.

The combined findings support a socio-technical view of AI adoption. Technological capability appears more acceptable when it is accompanied by governance mechanisms that preserve transparency, accountability, and professional judgment. The practical focus should therefore be on how firms design and control AI-enabled workflows rather than on automation as an end in itself.

4.4.3 Ethical Risk and Legal Exposure

Table 8 presents Model 3, which examines perceived legal exposure. Perceived ethical risk is positively associated with perceived legal exposure ($\beta = 0.5356$, $p < .001$), supporting H3. AI auditability has a negative but statistically nonsignificant direct coefficient after ethical risk and oversight design are included in the model ($\beta = -0.0916$, $p = .392$). The distinction between the bivariate and multivariate results is important: auditability is negatively correlated with legal exposure, but the evidence does not establish a statistically significant direct regression effect once ethical risk is controlled.

Table 8. Model 3. Predictors of Perceived Legal Exposure (LEGALEXP)

Variable	Coefficient	HC3 SE	T	P
Intercept	4.0323	0.6213	6.4897	<0.001
ETHRISK	0.5356	0.0766	6.9932	<0.001
AUDITAB	-0.0916	0.1069	-0.8560	0.392
AI-only	0.4191	0.0760	5.5132	<0.001
AI+HITL	-0.4845	0.0811	-5.9769	<0.001

The results therefore do not justify claiming a formally demonstrated mediation effect. A plausible interpretation is that ethical-risk perceptions are one mechanism through which auditability may be related to perceived legal exposure, but this pathway was not formally tested as a mediation model. The appropriate conclusion is limited to the observed associations: stronger auditability is

associated with lower legal-exposure perceptions at the bivariate level, while ethical risk remains a significant predictor in the multivariate model.

The oversight coefficients provide additional evidence about the role of governance design. Relative to manual-only auditing, AI-only auditing is associated with higher perceived legal exposure ($\beta = 0.4191$, $p < .001$), whereas AI-assisted + HITL is associated with lower perceived legal exposure ($\beta = -0.4845$, $p < .001$). These findings support H5 and H6 for legal-risk perceptions and are consistent with the vignette comparisons.

A reasonable interpretation is that human review and override authority make responsibility more visible and give professionals an opportunity to challenge AI-generated outputs before conclusions are finalized. This interpretation is consistent with the governance literature, but the experiment measures perceived legal exposure rather than actual litigation, regulatory action, or liability. The Ghanaian legal context reinforces the importance of data protection, cybersecurity, and accountability, but the present data cannot establish that any particular governance arrangement prevents a legal violation.

Table 9. Model Fit Statistics

Model	N	R ²	Adjusted R ²	F-statistic	Prob > F
Model 1 (Ethical Risk)	180	0.693	0.665	25.83	<0.001
Model 2 (Legal Exposure)	180	0.805	0.789	49.18	<0.001
Model 3 (Audit Quality)	180	0.706	0.684	45.75	<0.001

All three regression models are statistically significant. Model 1 explains 69.3% of the variance in perceived ethical risk (adjusted $R^2 = .665$), Model 2 explains 80.5% of the variance in perceived legal exposure (adjusted $R^2 = .789$), and Model 3 explains 70.6% of the variance in perceived audit quality (adjusted $R^2 = .684$). These fit statistics indicate substantial explanatory power within the sample, but they should not be interpreted as evidence of causal effects or generalizable population-level prediction.

4.5 Experimental Findings: Oversight Design and Risk Perception

The vignette experiment provides the clearest evidence about oversight design. Respondents in the AI-only condition reported the highest perceived ethical and legal risk, while those in the AI-assisted + HITL condition reported the lowest. Manual-only auditing generally fell between the two. The ANOVA and post-hoc results show statistically significant differences for ethical risk and legal exposure, but not for audit quality.

These findings suggest that professionals distinguish between AI used as an autonomous decision mechanism and AI embedded within a workflow where human reviewers retain responsibility and override authority. This pattern is consistent with the socio-technical perspective: the same broad technological capability can be perceived differently depending on the human and organizational controls surrounding it. The experiment does not, however, demonstrate that HITL oversight improves actual audit outcomes; it demonstrates that the stated oversight arrangement changes professional perceptions of risk.

A manipulation check was included in the questionnaire to assess whether respondents recognized their assigned oversight condition. The current manuscript reports that these questions were included but does not provide the resulting statistics. Before submission, the authors should report the manipulation-check test, including the test statistic, degrees of freedom, p-value, and an appropriate effect-size measure, or the relevant group means if the check was descriptive. The result should be presented separately from the substantive outcome tests.

4.6 Implications for Practice and Policy

The findings have practical implications for audit firms, regulators, and professional bodies. For audit firms, the evidence supports embedding AI governance into audit workflows through documentation, traceability, explainability, model validation, access controls, and explicit human review and override procedures. The aim should be to make AI-supported judgments reviewable and defensible rather than simply faster. Firms should also train staff in AI governance, data ethics, cybersecurity, bias risks, and professional skepticism.

For regulators and professional bodies in Ghana, the findings support clearer guidance on documentation, accountability, audit-trail preservation, explainability, and human oversight in AI-enabled assurance. International frameworks can provide useful reference points, but local guidance should be adapted to Ghana's statutory and professional environment. These implications are grounded in perceived risk and quality; they should not be read as evidence that a particular control is legally sufficient in every engagement.

5. Conclusion and Recommendations

5.1 Conclusion

This study examined how AI auditability and oversight design are associated with assurance professionals' perceptions of ethical risk, legal exposure, and audit quality in Ghana. The evidence indicates that stronger perceived AI auditability is associated with lower perceived ethical risk and higher perceived audit quality. Ethical risk is, in turn, positively associated with perceived legal exposure and negatively associated with perceived audit quality. At the bivariate level, AI auditability is negatively related to legal exposure, but its direct regression effect is not statistically significant after ethical risk is controlled.

The vignette experiment adds an important governance perspective. AI-only auditing generated substantially higher perceptions of ethical and legal risk than manual-only auditing, while AI-assisted auditing with HITL oversight generated substantially lower risk perceptions than AI-only auditing. The experimental evidence therefore points to oversight design as an important determinant of how professionals evaluate AI-related risk. However, the study measures perceptions rather than actual legal outcomes, realized audit quality, or observed organizational performance.

Taken together, the findings support a governance-centered approach to AI adoption in auditing. AI should not be evaluated only in terms of automation or analytical capability. Its value also depends on whether auditors can trace and understand its outputs, document how it is used, and exercise meaningful professional judgment over consequential decisions. This conclusion is consistent with both Risk Governance Theory and Socio-Technical Systems Theory.

The study contributes to the literature by extending empirical evidence on AI governance and auditability into the Ghanaian assurance environment. It also shows that professionals appear more comfortable with AI when human accountability remains visible and operational. The practical message is therefore straightforward: responsible AI adoption requires governance arrangements that make the technology reviewable, explainable, and accountable.

5.2 Recommendations

Audit firms should treat AI governance as part of audit methodology rather than as a separate technology project. They should maintain model and data documentation, preserve traceable audit trails, use appropriate explainability mechanisms, define responsibility for AI-supported judgments, and require meaningful human review for higher-risk applications. Firms should also monitor AI systems throughout their lifecycle and provide continuous training in AI governance, data ethics, cybersecurity, algorithmic bias, explainability, and professional skepticism.

Professional accounting bodies and regulators should develop practical guidance for AI-enabled assurance, covering accountability, documentation, explainability, audit-trail preservation, model governance, and human-review expectations. ICAG can play an important role through continuing professional development and technical guidance on digital assurance. International frameworks such as the EU AI Act, NIST AI RMF, and OECD AI Principles can inform this work, but implementation should remain sensitive to Ghana's legal and institutional context.

Policymakers should also consider coordination across data protection, cybersecurity, professional regulation, and financial-reporting institutions as AI use expands. National guidance should promote responsible data governance, cybersecurity safeguards, transparency, and clear accountability for AI-enabled professional services.

5.3 Limitations

This study has some limitations. First, the cross-sectional survey design limits causal interpretation of the observed relationships. Second, the sample was obtained through purposive, quota-based, convenience, and referral recruitment rather than probability sampling, which limits generalizability to the full population of Ghanaian assurance professionals. Third, the principal outcomes are perceptual measures; they capture how respondents assess ethical risk, legal exposure, and audit quality rather than actual litigation, regulatory sanctions, audit deficiencies, or realized engagement quality.

Future research should use longitudinal designs, probability or broader multi-firm samples where feasible, and objective organizational indicators of AI governance and audit outcomes. Comparative studies across African jurisdictions could also clarify how differences in legal and professional environments shape AI-related risk perceptions. Mediation analysis could formally test whether ethical risk statistically mediates the relationship between AI auditability and perceived legal exposure, an inference that the present study does not establish.

References

- Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with Computers*, 23(1), 4–17. <https://doi.org/10.1016/j.intcom.2010.07.003>
- DeAngelo, L. E. (1981). Auditor size and audit quality. *Journal of Accounting and Economics*, 3(3), 183–199. [https://doi.org/10.1016/0165-4101\(81\)90002-1](https://doi.org/10.1016/0165-4101(81)90002-1)
- European Union. (2024). *Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*. *Official Journal of the European Union*. <https://eur-lex.europa.eu/eli/reg/2024/1689/oj>
- Farley, E. A., & Lansang, C. R. (2025). AI auditing: First steps towards the effective regulation of artificial intelligence systems. *Harvard Journal of Law & Technology Digest*, 38. <https://jolt.law.harvard.edu/digest/ai-auditing-first-steps-towards-the-effective-regulation-of-artificial-intelligence-systems>
- Francis, J. R. (2011). A framework for understanding and researching audit quality. *Auditing: A Journal of Practice & Theory*, 30(2), 125–152. <https://doi.org/10.2308/ajpt-50006>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2022). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer. <https://doi.org/10.1007/978-3-030-80519-7>
- International Auditing and Assurance Standards Board. (2024). *2023–2024 handbook of international quality management, auditing, review, other assurance, and related services*

- pronouncements*. International Federation of Accountants. <https://www.iaasb.org/publications/2023-2024-handbook-international-quality-management-auditing-review-other-assurance-and-related>
- International Ethics Standards Board for Accountants. (2024). *2024 handbook of the international code of ethics for professional accountants (including international independence standards)*. International Federation of Accountants. <https://www.ethicsboard.org/publications/2024-handbook-international-code>
- Langer, M., Oster, J., & König, C. J. (2024). Effective human oversight of AI-based systems: A signal detection theory perspective. *AI & Society*. Advance online publication. <https://doi.org/10.1007/s00146-024-01788-y>
- Li, Y., & Goel, S. (2025). Artificial intelligence auditability and auditor readiness for auditing artificial intelligence systems. *International Journal of Accounting Information Systems*, 56, 100739. <https://doi.org/10.1016/j.accinf.2025.100739>
- Libby, R., & Witz, P. (2024). Artificial intelligence in auditing: How auditor AI use can mitigate legal liability. *Current Issues in Auditing*, 18(3), 1–11. <https://doi.org/10.2308/CIIA-2024-029>
- Morley, J., Floridi, L., Kinsey, L., & Elhalal, A. (2021). From what to how: An initial review of publicly available AI ethics tools, methods and research to translate principles into practices. *Science and Engineering Ethics*, 27(1), 1–22. <https://doi.org/10.1007/s11948-020-00239-w>
- Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. *Journal of Business Ethics*, 167(2), 209–234. <https://doi.org/10.1007/s10551-019-04407-1>
- Murikah, W., Nthenge, J. K., & Musyoka, F. M. (2024). Bias and ethics of AI systems applied in auditing—A systematic review. *Scientific African*, 25, e02281.
- National Institute of Standards and Technology. (2023). *Artificial intelligence risk management framework (AI RMF 1.0)* (NIST AI 100-1). U.S. Department of Commerce. <https://doi.org/10.6028/NIST.AI.100-1>
- Organisation for Economic Co-operation and Development. (2024). *OECD AI principles*. <https://oecd.ai/en/ai-principles>
- Renn, O. (2008). *Risk governance: Coping with uncertainty in a complex world*. Earthscan.
- Republic of Ghana. (2012). *Data Protection Act, 2012 (Act 843)*.
- Republic of Ghana. (2020). *Cybersecurity Act, 2020 (Act 1038)*.



Schiff, D. S., Kelley, M. M., & Camacho Ibáñez, J. (2024). The emergence of artificial intelligence ethics auditing. *Big Data & Society*, 11(4), 1–16.
<https://doi.org/10.1177/20539517241299732>