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The Applicability of Manual-Based IIA Global Standards in AI-Driven Internal Auditing: A Bridging-Gap Systematic Literature Review

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ABSTRACT

This paper examines whether and how the Institute of Internal Auditors' (IIA) manual-based Global Internal Audit Standards (the 2024 Standards, effective 9 Jan 2025) remain applicable when internal audit engages with AI-driven systems and processes. Using a systematic literature review (SLR) approach and a thematic synthesis of practitioner guidance, standards texts, and academic research, the paper maps the overlap between principle-based IIA Standards and AI auditing needs, identifies gaps where the manual (traditional) interpretation of Standards is strained by AI characteristics and proposes a pragmatic bridging framework (policy, practice and capability) for auditors, stakeholders, and standards-setters. Key findings: the IIA's Standards remain broadly relevant as high-level normative anchors, but practical application requires AI-specific procedural guidance, stronger access/transparency norms, and workforce upskilling; the IIA's AI Auditing Framework is a critical complementary resource but does not completely eliminate operational gaps calling for targeted Topical Requirements and coordinated standard-setting for AI assurance.

Introduction

The rapid adoption of AI in auditing signifies a transformative phase for the internal auditing profession. IIA has acknowledged this shift by issuing revised Global Internal Audit Standards, which are designed to guide auditors through the complexities brought on by AI and other emerging technologies. Effective from January 2025, these standards aim to enhance the quality and integrity of internal audits in an AI-driven environment (Seethamraju & Hecimovic, 2022; Kend & Nguyen, 2020). However, as AI technologies proliferate, various challenges such as model opacity, data quality concerns, and rapidly evolving regulatory expectations complicate the application of traditional auditing methodologies.

The distinction between automated solutions and the manual-based IIA Global Standards requires careful examination. Current standards were developed in environments with simpler data processing and less stringent compliance demands. This has led to a mismatch between the rapid advancement of AI technologies and the somewhat static nature of existing auditing standards (Kend & Nguyen, 2020). While AI-driven approaches can augment audit quality and efficiency, they pose inherent challenges particularly concerning the transparency and interpretability of AI models, often described as "black boxes" (Mpofu, 2023; Albawwat & Frijat, 2021). A thorough understanding of these AI systems and their outputs becomes critical for auditors to ensure accountability and ethical adherence.

Significant gaps exist in how the IIA Global Standards can be adapted to AI-driven environments. Although AI tools can enhance analytical capabilities and operational efficiency, many professionals struggle to trust these technologies due to their opacity and complexity in understanding their decision-making processes (Mpofu, 2023; Noordin, Hussainey, & Hayek, 2022). There is a sentiment among auditors that they are already at a disadvantage in comprehending AI applications, which may lead to reluctance in fully implementing these technologies (Noordin et al., 2022). Consequently, bridging these gaps necessitates the integration of continuous auditing practices that keep pace with AI's rapid evolution, thereby enabling auditors to monitor AI's performance effectively in real-time (Minkkinen et al., 2022; Lidiana, 2024).

Moreover, there is a broader recognition that AI audits need a robust framework. This entails not only regulatory compliance but also adherence to ethical standards established in AI applications. The existence of an accountability gap in AI deployment underscores the urgent need for a systematic audit process that evaluates the entire lifecycle of AI algorithms, from inception to deployment and ongoing operation (Raji et al., 2020; Ugwudike, 2021). External factors, such as the Big Four audit firms and standards bodies, are working to establish frameworks and guidelines for credible AI assurance, but these efforts are still in the early stages, indicating uneven standardisation across the field (Ayling & Chapman, 2021; Iwuanyanwu et al., 2023).
In summary, while the newly revised IIA Global Standards aim to provide a compliance framework for internal audit practices, their effectiveness in AI environments is currently affected by gaps in applicability and emerging challenges. A concerted effort is needed from both internal auditors and external governance bodies to develop actionable recommendations and comprehensive frameworks that address the practical implications of AI in auditing, ensuring that both quality and ethical standards are upheld.

Primary objective

Assess the applicability of the 2024 IIA Global Internal Audit Standards to AI-driven internal audit activities and identify the gaps and bridging mechanisms required for adequate assurance of AI systems.

Research questions

1. Which IIA Standards elements directly apply to AI auditing, and how?
2. What are the practical and conceptual gaps when applying manual-based Standards to AI systems?
3. What complementary guidance, access models, and capability changes are required to bridge these gaps?
4. What are the implications for future revisions of the Standards (e.g., Topical Requirements, Global Guidance)?

Theoretical framing and definitions

The contemporary landscape of AI auditing requires a nuanced understanding that incorporates normative principles and socio-technical perspectives. The application of AI in various fields, particularly in decision-making processes, necessitates a comprehensive audit framework that acknowledges the complexity inherent in AI systems. This complexity arises from the interplay of multiple factors, including technical models, datasets, human decisions, and the contexts in which these systems are deployed.

The principles-based approach to audit mandates adherence to foundational ethical standards, including roles, independence, objectivity, competence, and quality. These normative anchors are essential for establishing trust and accountability in AI applications, where the consequences of errors can be significant (Raji et al., 2020). The literature underscores that traditional auditing frameworks, which often focus heavily on compliance metrics, may not suffice when addressing the unique challenges posed by AI technologies (Schiff et al., 2024). This gap is increasingly recognised, leading to the assertion that black-box access—characterised by limited visibility into an AI's operational mechanics—is inadequate for ensuring rigorous assurance processes. Studies suggest that audits employing white-box methodologies enable a more robust examination of AI systems, allowing for greater scrutiny of the decision-making processes embedded within these technologies (Arora & Sarkar, 2023).

Moreover, socio-technical systems theory provides an essential lens through which to view these audits. The theory emphasises the interaction between technology and societal factors, highlighting how human decisions influence algorithmic outcomes (Yu et al., 2022). Recent discussions around AI ethics auditing indicate that auditors must not only evaluate technical risk but also consider relational dynamics among stakeholders and operational contexts. This multifaceted approach is crucial in identifying and mitigating risks pertaining to algorithmic bias and lack of transparency, which have emerged as paramount concerns in contemporary discourses on AI governance (Baobao et al., 2021; Giordani & Zeko, 2024).

An empirical understanding of AI auditing further illustrates that auditors face numerous practical challenges, such as staffing shortages and insufficient technical infrastructure. As highlighted by Raji et al. (2020), effective AI governance requires embedding audit integrity throughout the AI lifecycle, thereby closing the accountability gap. Furthermore, literature on the intersection of AI and ethics underscores the importance of engaging with relevant stakeholders to address these multifarious challenges. It advocates for more holistic audit frameworks that recognise the complexity of ethical considerations and the dynamic nature of AI applications in real-world scenarios (Brown et al., 2021).

Literature synthesis — What the literature shows

IIA Standards as normative anchors — applicability and strengths

The integration of AI within auditing practices, particularly in relation to the standards set forth by the IIA, is a critical area of exploration. The 2024 IIA Standards provide foundational principles namely independence, objectivity, professional competence, and risk-based planning that remain essential for all assurance activities, including AI ones. These principles serve as ethical and professional anchors, ensuring that auditors maintain high integrity and professionalism as they engage in AI auditing activities (Seethamraju & Hecimovic, 2022; Schiff et al., 2024).

Despite the foundational nature of these standards, their application must evolve to address the specific challenges presented by AI technologies. The IIA recognises this imperative by advocating for a topical domain structure that allows for expansion into AI-relevant topics, thereby ensuring that the standards remain applicable and relevant in the face of ongoing technological advancements (Fedyk et al., 2022; Bankins & Formosa, 2023). Moreover, the IIA has recently introduced an AI Auditing Framework designed explicitly to guide internal auditors through the challenges of AI-related issues, enabling them to navigate the complexities of this rapidly evolving field (Morley et al., 2021).

Current literature supports the assertion that while existing standards provide a necessary framework, their operationalisation is essential to effectively incorporate AI into auditing processes. For instance, the ability of AI systems to automate and enhance audit procedures corroborates the need for updated guidelines to ensure these advancements align with ethical practices (Lidiana, 2024). Moreover, audit quality is found to improve significantly with the adoption of AI technologies, underscoring the potential for AI to reshape traditional auditing landscapes while simultaneously raising ethical concerns that must be meticulously managed (Noordin et al., 2022; Mpofu, 2023).

It is also noteworthy that many audit firms value the existing standards as they pursue AI integration, while regulators view them as helpful but not mandatory (Seethamraju & Hecimovic, 2022; Minkkinen et al., 2022). This dual perspective indicates a growing recognition of the importance of ethical considerations in AI applications, emphasising the need for practices that monitor not only compliance but also fairness and accountability in AI systems (Falco et al., 2021; Iwuanyanwu et al., 2023). The development of frameworks for ethics-based AI auditing also reflects a broader commitment to addressing social biases and ensuring that AI technologies function equitably for all stakeholders (Raji et al., 2020; Bankins & Formosa, 2023).

Practical gaps when applying manual-based Standards to AI

The examination of gaps in AI auditing reveals critical areas across access and transparency, control design and evidence standards, and competence and tooling. These gaps are increasingly manifesting as organisations integrate AI into various functions but lack the necessary frameworks for rigorous oversight.

Access and Transparency

The effectiveness of AI assurance processes is largely contingent upon the level of transparency provided in the audits. Observations in current literature indicate that black-box audits, which typically analyse only inputs and outputs, are insufficient for uncovering deeper systemic risks associated with AI models, such as bias introduced through training data or errors in model development processes (Hond et al., 2022). The debate is significant regarding the necessity of white-box access, which allows for a more holistic review but brings forth concerns related to intellectual property and data security (Klaise et al., 2020). Calls for detailed examination highlight that rigorous audits necessitate insights into the model's inner workings and governance frameworks (Soin et al., 2022). Instances from healthcare contexts underline that transparency into machine learning model operations is fundamental for trust and reliability (Gupta et al., 2020).

Control Design and Evidence Standards

Traditional auditing methods fall short when applied to AI's continuously evolving, probabilistic output systems. The literature suggests a pressing need for a paradigm shift in evidence standards to include modern data governance practices, model validation frameworks, and ongoing monitoring of model performance (Biagi & Russo, 2022). Evidence from systems such as AI-driven healthcare predictions shows that control definitions must evolve beyond conventional transaction sampling and walkthroughs (Hond et al., 2022). Furthermore, external validation studies indicate that the comprehensive assessment of such models must extend into their deployment settings, considering calibration and discrimination performance (Yamada et al., 2021). The historical reliance on familiar auditing techniques renders them inadequate in the context of dynamic AI models, necessitating a framework that aligns evidence collection and validation with the unique features of AI (Chou et al., 2023).

Competence and Tooling

A prevailing challenge within audit teams is the lack of requisite data science expertise that hampers the effective integration of AI audits within organisations (Hond et al., 2022). Research emphasises the urgent need for upskilling internal auditor capabilities and adopting collaborative models, such as co-sourcing or embedding data scientists within audit teams, to bridge this competency gap (Li, 2023). This approach enhances the interpretative skills necessary to understand complex AI models and fosters a culture of continuous learning about data governance and AI deployment standards (Makrygiorgos et al., 2023). Efforts to create a cross-disciplinary audit framework are thus recommended, where a deeper interdisciplinary understanding could lead to refined metrics and tools for overseeing AI systems (Klaise et al., 2020).

Standards vs. AI auditing frameworks — complementary, not redundant

The integration of AI within internal auditing frameworks is increasingly relevant in today's evolving technological landscape, demanding meticulous attention to governance, competencies, data quality, and algorithmic transparency. The International Internal Audit Standards Board (IIASB) recognises the significance of incorporating AI considerations into existing auditing standards. However, the frameworks and guidance surrounding AI auditing remain emergent and inconsistent across various sectors. Diverse players in industry and regulatory environments are concurrently developing guidance and assurance models, contributing to a fragmented assurance landscape that necessitates harmonisation.

Recent studies explore these themes, highlighting the importance of establishing robust governance practices for AI in auditing. Hu et al. (2023) argue that effective governance mechanisms can facilitate the assessment of AI applications in business audits, thereby enhancing the reliability of audit results and addressing ethical concerns associated with AI systems. Furthermore, Mökander et al. (2023) emphasise the relevance of a three-layered approach in auditing large language models (LLMs), where systematic auditing acts as a governance mechanism to mitigate risks related to AI systems. This aligns with the notion that auditing must now encompass both technical and process-oriented perspectives, as articulated by Mökander (2023), which recognises the multiplicity of approaches in this domain.

Wassie and Lakatos (2024) examine the fragmentation in assurance landscapes noting that AI's potential to enhance the internal audit function is contingent upon navigating this complexity with well-defined frameworks and strategies. In an environment featuring varying frameworks for AI governance, industry actors are challenged to synthesise these composite assurance models efficiently. This is echoed by Schuett (2024), who highlights the critical need for internal audit functions within AI development enterprises to provide clarity and a regulatory roadmap. The calls for standardised frameworks become even more compelling when examining the ethics-based approaches to auditing automated decision-making systems, as discussed by Mökander et al. (2021).

Moreover, the increased demand for transparent and accountable AI systems is underscored by research advocating for independent audits that incorporate principles of accountability, transparency, and risk assessment, known as the "AAA" principles (Falco et al., 2021). Establishing and enforcing such auditing standards are pivotal in navigating the complexities of AI governance, ensuring that implementations align with ethical standards and regulatory requirements, as articulated in the literature (Schiff et al., 2024).

Challenges of AI in Internal Auditing

Although AI offers transformative potential for internal auditing, enhancing efficiency, analytical capacity, and risk anticipation. It simultaneously presents notable challenges when evaluated through the lens of the IIA Global Standards. These challenges underscore the need to critically assess whether manual-based standards remain fully applicable in AI-driven audit environments.

Data Governance and Reliability

AI-enabled audits depend on vast and complex datasets. The integrity, accuracy, and completeness of these data sources directly influence the reliability of audit outcomes. This reliance challenges the auditor’s ability to apply Standard 2310 (“Identifying Information”) effectively, as traditional verification procedures may be inadequate for algorithmically processed data.

Transparency and Explainability of AI Models

Many AI tools, particularly those employing machine learning, function as “black boxes,” where decision logic is not transparent. This lack of transparency can hinder compliance with Standard 1220 (“Due Professional Care”), which requires auditors to understand and evaluate the processes underlying their conclusions. Without interpretability, ensuring audit assurance and accountability becomes problematic.

Ethical and Governance Implications

The ethical considerations surrounding AI—such as bias, privacy, and fairness—extend beyond technical performance. Aligning with Standard 2110 (“Governance”), internal auditors must ensure that AI systems are implemented responsibly, with clear governance structures and ethical safeguards. This requires new forms of oversight that go beyond the manual-based control frameworks traditionally used.

Competency and Professional Proficiency

The integration of AI necessitates new skill sets related to data science, algorithmic reasoning, and digital ethics. Standard 1210 ("Proficiency") highlights the need for auditors to possess the necessary knowledge and competencies to carry out their responsibilities. The growing technical complexity of AI systems challenges auditors to continuously update their expertise to maintain professional relevance.

Lastly, while the IIA's manual-based Global Standards provide a strong foundation for professional internal auditing, their application in AI-driven contexts requires reinterpretation and, in some cases, adaptation. Recognising and addressing these challenges is essential to ensuring that the Standards remain both authoritative and practical in guiding assurance activities within an increasingly digital audit environment.

Methodology — Systematic Literature Review (SLR)

Databases searched: Web of Science, Scopus, IEEE Xplore, ACM Digital Library, PubMed/PMC, ScienceDirect, Google Scholar, and practitioner sources (IIA website, Big Four insights, FT, Reuters). (Representative sources are cited below.)
Time window: 2015–2025 (to capture recent surge in AI auditing literature and the 2024 IIA Standards).
Search strings (examples): "internal audit" AND "artificial intelligence", "AI auditing", "audit of AI", "IIA" AND "standards" AND "AI", "algorithmic audit" AND "internal audit".
Inclusion criteria: peer-reviewed papers, whitepapers, IIA materials, reputable industry reports, and policy papers addressing AI auditing, governance, standards, or internal audit roles. English language.
Exclusion criteria: purely technical ML model papers without an audit/governance angle, blog posts without referenced evidence, duplicates.
Screening and synthesis: title/abstract screening → full text review → thematic coding (NVivo or manual codebook) to extract themes related to Standards applicability, access/transparency, governance, controls, competencies, and legal/regulatory challenges.
Reporting: follow PRISMA flow for selection; synthesise via narrative synthesis and conceptual mapping

Discussion — Bridging the gap

The overarching conclusion is that the IIA Standards remain applicable but incomplete for AI auditing. Three bridging strategies are proposed:

Operationalise Standards with AI-specific Topical Requirements: The Standards' architecture allows Topical Requirements to become mandatory elements. The profession would benefit from a formal Topical Requirement (or set) that prescribes minimum expectations for AI assurance (access levels, model documentation, data governance evidence, monitoring expectations). This should be developed in partnership with technical standard bodies (e.g., NIST) to avoid duplication.

Define clear access & evidence models: Standards or guidance should include an access taxonomy (black/white/outside) and describe how each affects evidence sufficiency. Quality assessors should have explicit guidance on how to judge conformance when full white-box access is not possible (e.g., reliance on third-party attestations, independent model challenge protocols). Literature warns that black-box alone is insufficient for rigorous assurance—standards should reflect this.

Capability & tooling requirements: The IIA Standards' competence expectations must be interpreted to include demonstrable AI-related capabilities (data lineage understanding, model validation knowledge). Organisational guidance for staffing, training, and relationships with data science functions is necessary.

Practical recommendations (for practitioners & standards bodies)

Internal audit functions:

- Update risk-based audit plans to explicitly include AI systems and their lifecycles; use IIA's AI Auditing Framework as an operational guide.
- Classify AI systems by risk profile (impact, autonomy, scale) and apply proportionate assurance intensity (e.g., white-box for high-impact systems).
- Invest in core capabilities (training, tooling, data scientists) and establish pre-engagement checklists for model access.

Integrate AI Risk into Enterprise Risk Management (ERM): AI-related risks (e.g., model drift, data poisoning, adversarial attacks) should be explicitly mapped within the ERM framework. Internal audit should collaborate with risk management teams to ensure AI risks are continuously monitored and reassessed.
Develop AI Audit Playbooks: Create internal audit playbooks tailored to different AI system types (e.g., supervised learning, reinforcement learning, generative models). These should include audit objectives, key risk indicators, access protocols, and evidence expectations.
Establish AI Audit Readiness Assessments: Before engaging in AI audits, conduct readiness assessments to evaluate the maturity of AI governance, documentation, and explainability. This helps scope the audit and identify capability gaps early.
Adopt Continuous Auditing for AI Systems: Implement real-time or near-real-time monitoring tools to track AI system performance, fairness, and compliance. This is particularly important for high-frequency or high-impact AI applications.
Foster Cross-Functional Collaboration: Build audit teams that include data scientists, ethicists, and legal experts. This interdisciplinary approach ensures that audits address technical, ethical, and regulatory dimensions of AI.

The IIA and standards-setters:

Consider formal Topical Requirements for AI assurance (minimum attributes, evidence models). including: Minimum documentation standards (e.g., model cards, data sheets)

- Explainability thresholds
- Audit trail requirements for AI decision-making
- Model lifecycle governance (development, deployment, monitoring, retirement)

- Collaborate with technical standard bodies (NIST AI RMF and others) to harmonise assurance criteria.

Issue AI-Specific Topical Requirements and Practice Guides**:** Develop mandatory Topical Requirements for AI assurance, Create a Global AI Assurance Maturity Model:
This model would help internal audit functions benchmark their AI assurance capabilities across dimensions such as governance, tooling, skills, and integration with business processes.

Promote AI Audit Certification Tracks: Introduce AI-focused certifications or micro-credentials for internal auditors (e.g., "Certified AI Internal Auditor") to formalise competence development. Facilitate Knowledge-Sharing Platforms: Establish global forums or knowledge hubs where auditors can share AI audit case studies, tools, and lessons learned. This would accelerate learning and standardisation.

Regulators and boards

Encourage transparency requirements for AI suppliers to facilitate auditable access; consider regulatory expectations for AI auditability where public interest is high.

Mandate AI Auditability in High-Risk Sectors: For sectors like healthcare, finance, and public services, regulators should require that AI systems be auditable by design. This includes mandatory documentation, access protocols, and third-party audit provisions.
Incentivise Ethical AI Practices through Governance Ratings: Encourage ESG (Environmental, Social, Governance) rating agencies to include AI governance and auditability as part of their scoring criteria. This would create market incentives for responsible AI deployment.
Support Regulatory Sandboxes for AI Auditing: Create safe environments where internal auditors can test AI audit techniques and tools in collaboration with regulators and AI developers, without fear of punitive consequences. **Align with International AI Governance Frameworks:** Encourage harmonisation with global initiatives such as the OECD AI Principles, EU AI Act, and NIST AI Risk Management Framework to ensure consistency and reduce compliance burdens.

Limitations

This paper is a narrative synthesis based on a targeted SLR protocol; it does not present a quantitative meta-analysis or a completed PRISMA flow for a replicable database extraction in this draft. The field is rapidly evolving: new guidance, audits, and regulations may have emerged after this draft. Where possible, the paper has cited contemporary guidance and high-impact literature.

Conclusion

The 2024 IIA Global Internal Audit Standards continue to be the appropriate normative foundation for internal audit's engagement with AI. However, their manual-based, high-level nature means they must be complemented by AI-specific operational guidance, clarified access/evidence models, and capability upgrades within audit functions. The IIA's AI Auditing Framework is an important practical companion but does not fully substitute for mandatory Topical Requirements and harmonised assurance rules. Coordinated action—practical guidance for auditors, clearer expectations for evidence and transparency, and investments in skills—is required to bridge the gap between manual-based Standards and the realities of AI-driven auditing.

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