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HUMAN–AI SYNERGY IN AUDITING: A SYSTEMATIC REVIEW OF EMERGING EVIDENCE ON AUDIT QUALITY

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Abstract:

This systematic literature review explores the interplay between artificial intelligence (AI) and human capital in shaping future audit quality. Using the PRISMA framework, 33 peer-reviewed articles from Scopus and Web of Science (2021–2025) were analysed to assess how AI capabilities and human expertise jointly influence audit outcomes. Findings reveal that AI technologies, particularly machine learning and data analytics, significantly improve audit efficiency, accuracy, and risk detection. However, human capital remains essential for sustaining professional qualities such as scepticism, ethical judgment, and client trust. The review identifies five key themes: (1) auditors' competencies in the AI era, (2) AI adoption and readiness in audit firms, (3) AI's impact on audit quality and reporting, (4) AI-driven audit models and methodologies, and (5) governance, ethics, and auditability of AI. The study concludes that optimal audit quality depends on integrating AI's technical strengths with human critical thinking and ethical decision-making. Practical implications emphasise strategic investment in auditor training, organisational readiness, and governance frameworks to enable effective human-AI collaboration. This research offers an integrative perspective, positioning the synergy between technology and human expertise as the cornerstone for advancing audit practices and ensuring high-quality outcomes in the evolving digital landscape.

Keywords:

Human Capital; Artificial Intelligence; Auditing; Audit Quality; AI Governance

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Introduction

Over the past years, the development of technology, especially Artificial Intelligence (AI), has been a transformative force across various industries, including the auditing profession (Hasan, 2022; Malouin, 2020). At the same time, human capital remains a key factor in determining audit quality, encompassing auditors' knowledge, experience, ethical considerations, and decision-making skills (Brey & van der Marel, 2024). As businesses increasingly operate in more complex and data-intensive settings, the intersection between human capital and AI is emerging as a focal point of debate on how to sustain and enhance audit quality (Kusumaningrum et al., 2022). The dynamics between these two forces are timely and essential to regulators, practitioners, and scholars seeking to ensure the integrity and reliability of financial reporting in a digital world.

The current literature offers a nuanced assessment of the impact of human capital and AI on audit outcomes, both individually and in combination. Research findings have repeatedly shown that professional skepticism, judgment, and flexibility help skilled auditors to play a vital role in audit quality (Fedyk et al., 2022; Knechel et al., 2012; Lamboglia & Mancini, 2021). Conversely, new literature notes the possibility of AI to improve the audit process through the automation of routine tasks, anomaly detection, and analysis of large amounts of data, faster and more accurately than ever before (Beryl et al., 2024; Ganapathy, 2023; Olubusola et al., 2023). AI is expected to be more efficient and accurate, but other researchers warn that its use can unintentionally reduce the quality of critical thinking or become overdependent on algorithms, thereby introducing new types of audit risk (Mitan, 2024). Also, recent studies are investigating the complementarities between human auditors and AI systems, which implies that future audit success is achieved through synergistic cooperation, as opposed to replacement (Kuncoro et al., 2023; Olubusola et al., 2023).

Despite these developments, several unresolved problems remain in the literature. It is essential to acknowledge that the empirical evidence regarding the impact of AI integration on audit quality across various contexts and jurisdictions remains insufficient. The issue of whether AI is capable of actually replicating or improving the subtle judgment of seasoned auditors is still more of a hypothetical one (Barr-Pulliam et al., 2024) Additionally, the organisational and ethical issues related to the implementation of AI, such as algorithm bias, data privacy, and the skills that auditors will need to develop, have received little focus (Mitan, 2024). Moreover, the active interaction between the development of human capital, including continuous learning and adaptation, and the use of AI is under-researched. Future studies should aim to fill these gaps through longitudinal and interdisciplinary research that considers both technical and behavioural factors, as well as institutional factors. Therefore, to prevent the risks of AI misuse, audit firms and policymakers need to invest in the upskilling of professionals and encourage an ethical system of AI application (Anomah et al., 2024; Malouin, 2020). This ensures that human judgment and machine intelligence work together to maintain the quality of the audit in a more digital audit environment.

Literature Review

The integration of AI in auditing has been a transformative force, significantly impacting audit quality. This literature review examines the dual role of AI and human capital in enhancing audit quality, with a focus on the efficiency, accuracy, and reliability of audit processes. The review synthesises findings from various studies to provide a comprehensive understanding of how AI and human capital investments shape the future of auditing.

AI's Impact on Audit Quality

AI has been demonstrated to profoundly enhance audit quality by improving accuracy, efficiency, and objectivity. Studies indicate that AI adoption is essential for auditors to meet time constraints, accuracy requirements, and job speed demands (Shazly, AbdElAlim, et al., 2025). AI technologies, such as machine learning and natural language processing, enable auditors to process large volumes of data quickly and accurately, reducing the likelihood of errors and enhancing the reliability of financial reporting (Al-Omush et al., 2025; Qader & Cek, 2024). Empirical evidence suggests that AI investments lead to a significant reduction in audit restatements and fees, highlighting its role in improving audit quality (Fedyk et al., 2022). However, the deployment of AI in auditing must be closely monitored to address potential challenges, such as data security and the need for appropriate training and governance (Shazly et al., 2025).

Human Capital and AI Integration

Human capital refers to the collective knowledge, skills, competencies, experience, and attributes embodied in individuals that contribute to organisational productivity and performance (Bontis & Fitz-enz, 2002). Furthermore, research by Earnest et al. (2015) revealed that human capital attributes, including intelligence, skills, knowledge, aptitudes, and expertise, contribute significantly to enhanced firm performance. The role of human capital in the successful integration of AI in auditing cannot be overstated. The effectiveness of AI in auditing depends on the skills and expertise of the auditors who implement and manage these technologies. Additionally, studies reveal that AI human capital, measured by the proportion of employees with AI-related skills, significantly enhances data processing efficiency and accuracy in firms (Liu & Zhang, 2025). However, a notable gap exists between the anticipated and actual use of AI in internal auditing, with challenges such as a shortage of qualified professional staff and inadequate technological support hindering the full adoption of AI (Ghozi, 2024). Hence, to bridge this gap, it is crucial to invest in training programs that equip auditors with the necessary skills to leverage AI technologies effectively (Chen et al., 2022; Yang et al., 2021)

Challenges and Future Directions

Despite the promising benefits of AI in auditing, several challenges must be addressed to maximize its potential. Data security concerns, ethical implications, and the need for robust governance frameworks are critical issues that must be addressed (Abouraia, 2024; Akbar et al., 2024). Additionally, the transition to AI-driven auditing necessitates a strategic approach that strikes a balance between technological capabilities and human expertise. Future research should focus on optimising the synergy between AI and human auditors, ensuring that AI tools are user-friendly and that auditors are empowered to integrate these tools into their practices (Benhayoun et al., 2025). Moreover, continuous skill development initiatives and ethical guidelines are essential to ensure responsible AI deployment and sustainable growth in the auditing profession (Abouraia, 2024). Table 1 illustrates a summary of existing studies.

Table 1: Summary Table from Existing Studies

Aspect	Findings	Sources
AI's Impact on Audit Quality	• Enhances accuracy, efficiency, and objectivity • Reduces audit restatements and fees • Requires close monitoring and governance	(Al-Omush et al., 2025; Fedyk et al., 2022; Qader & Cek, 2024; Shazly et al., 2025)
Human Capital and AI Integration	• AI human capital improves data processing efficiency • Gap between anticipated and actual AI use • Need for training programs	(Ghozi, 2024; Guo et al., 2012; Liu & Zhang, 2025; Wang & Zhu, 2024)
Challenges and Future Directions	• Data security and ethical concerns • Need for robust governance frameworks • Importance of balancing AI with human expertise	(Abouraia, 2024; Akbar et al., 2024; Benhayoun et al., 2025)

Source: Author's own compilation

In conclusion, the integration of AI in auditing holds significant potential for enhancing audit quality. Nonetheless, the successful implementation of AI technologies requires a strategic focus on human capital development, robust governance, and addressing ethical and security concerns. By optimising the synergy between AI and human auditors, the auditing profession can achieve greater accuracy, efficiency, and reliability in financial reporting

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Materials And Methods

Identification

In this study, the essential steps of the systematic review process were employed to compile a substantial body of relevant literature. The process commenced with the selection of keywords, followed by the exploration of related terms through dictionaries, thesauri, encyclopedias, and previous research. All pertinent terms were identified, leading to the creation of search strings for the Web of Science (WoS) and Scopus databases (see Table 2). Although 'human capital' was not used as a separate search term, this review applies a human capital lens when selecting, coding, and synthesising studies. Articles that discuss skills, competencies, expertise, training, or workforce aspects in the context of AI and audit quality were included. This initial phase of the systematic review resulted in the identification of 496 publications relevant to the study topic across the three databases. In conducting a Systematic Literature Review (SLR) following the PRISMA framework, the identification phase represents the foundational step, wherein relevant records are collected from various databases. In this study, the Scopus and WoS databases were employed, yielding a combined total of 496 records. Specifically, 395 records were identified through Scopus, while 101 were sourced from WoS. These databases were selected for their comprehensive coverage of academic journals and scholarly articles, making them highly suitable for identifying literature in the fields of AI and audit quality. Notably, Scopus is widely regarded for its vast interdisciplinary coverage, while WoS is a leading source for high-impact journals, particularly in the fields of management, economics, and technology. The dual approach of using both Scopus and WoS ensures a broad spectrum of high-quality sources, enhancing the reliability and depth of the review.

Table 2: The Search String

Scopus	(TITLE-ABS-KEY(("artificial intelligence" OR AI) AND audit QUALITY AND auditor) AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English")) AND (LIMIT-TO (SUBJAREA,"BUSI")) AND (LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2022) OR LIMIT-TO (PUBYEAR,2023) OR LIMIT-TO (PUBYEAR,2024) OR LIMIT-TO (PUBYEAR,2025)) Date of Access: September 2025
Wos	(("artificial intelligence" OR AI) AND audit quality AND auditor AND skill AND competencies AND audit*)) (Topic) and Article (Document Types) and English (Languages) and 2025 or 2024 or 2023 or 2022 or 2021 (Publication Years) and Business Finance or Management (Web of Science Categories) Date of Access: September 2025

Screening

The screening process in a systematic literature review (SLR) is vital for refining the initial pool of identified records. After the identification phase, records from Scopus and WoS were screened, resulting in the retention of 45 articles, 28 from Scopus and 17 from WoS. This reduction was achieved using predefined inclusion and exclusion criteria to ensure only the most relevant, high-quality articles were included. Key exclusion criteria included language (removing non-English records), publication dates (excluding articles published before 2021), and document types (omitting conference papers, books, and review articles, which typically do not present original research). Articles labelled as "in press" were also excluded due to concerns about incomplete peer review. These criteria prioritise recent, peer-reviewed studies that meaningfully contribute to understanding artificial intelligence (AI) in audit quality, enhancing the review's methodological rigour.

After excluding irrelevant records, an additional step removed 3 duplicates across the two databases, addressing overlap between Scopus and WoS. This step is essential to ensure unique contributions from each article and maintain the review's integrity. With 42 unique articles remaining, the literature is now more focused, representing high-quality studies that meet the established criteria. This careful screening process ensures the review accurately reflects the intersections of AI and audit quality, positioning it to provide valuable insights into AI's evolving role in enhancing audit practices.

Table 3: The Selection Criterion Is Searching

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	2021 - 2025	< 2021
Literature type	Journal (Article)	Conference, Book, Review
Subject	Business, Management, and Accounting	Besides Business, Management, and Accounting

Eligibility

The following step, known as the eligibility phase, involved preparing a total of 42 articles for review. During this stage, the titles and key content of each article were carefully examined to ensure they met the inclusion criteria and aligned with the current research objectives. As a result, 9 articles were excluded because they did not meet the criteria. This included those that were outside the relevant field, had titles not significantly related to the study's objectives, or lacked full-text access to empirical evidence. Consequently, only 33 articles remain for the upcoming review (Table 3).

Data Abstraction and Analysis

An integrative analysis was employed as one of the assessment strategies in this study to examine and synthesise a range of research designs, with a primary focus on qualitative methods. The primary objective of this approach was to identify relevant topics and subtopics. To begin with, the data collection phase marked the initial step in developing themes. As illustrated in Figure 1, the authors carefully analyse a compilation of 33 publications, extracting assertions and material relevant to the research focus of the current study. Following this, the authors reviewed significant studies related to AI, human capital and audit quality, carefully examining the methodologies used and the outcomes of these studies. Subsequently, the authors

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collaborated with co-authors to develop themes grounded in the evidence gathered in the context of this study. Throughout the data analysis process, a log was maintained to document any analyses, viewpoints, questions, or other reflections pertinent to the interpretation of the data. Correspondingly, the authors compared the results to identify any inconsistencies in the thematic development process. It is important to note that, in cases of disagreement over concepts, the authors engaged in discussions to resolve any discrepancies and ensure a coherent, consistent framework for the study's themes. Furthermore, the expert review phase helped ensure the clarity, importance, and adequacy of each sub-theme by establishing domain validity. Lastly, adjustments were made at the author's discretion, along with feedback and comments from experts. The questions are as follows:

1. How is the auditor's role changing due to AI, and what human skills are now essential to preserve audit quality and trust?
2. What factors most significantly influence the successful adoption of AI in audit firms?
3. How does the adoption of AI in auditing impact audit quality and efficiency across different contexts?
4. To what extent do AI-driven audit methodologies enhance detection accuracy and operational efficiency compared to traditional auditing techniques?
5. How can effective governance frameworks ensure AI tools in auditing are ethical, transparent, and auditable?

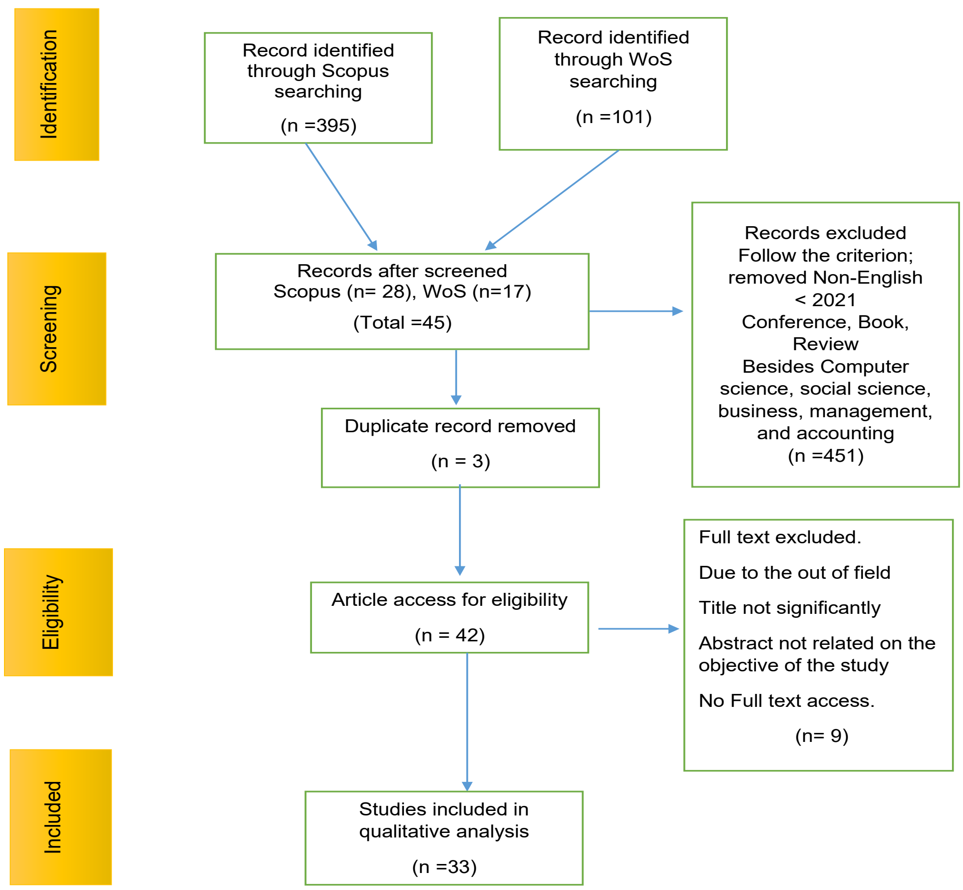

Figure 1: Flow Diagram of The Proposed Searching Study

Results and Discussion

Human Capital and Auditors' Competencies in the AI Era

The introduction of artificial intelligence into auditing has reshaped auditors' professional scepticism and judgment. Studies highlight that auditors perceive AI as a useful complement, but concerns remain over the extent to which human judgment can be substituted by algorithmic decision-making. For example, research in Oman revealed that auditors recognise AI's contribution to efficiency but caution against excessive reliance, as it may undermine the professional scepticism required for high-quality audits (Puthukulam et al., 2021). Similarly, investigations into complex estimation tasks reveal that auditors tend to rely more on AI outputs when facing uncertainty, although such reliance can potentially compromise independent judgment if not carefully managed (Commerford et al., 2022). These findings collectively suggest that while AI enhances technical capacity, it simultaneously raises questions about the evolving role of human capital in sustaining critical audit competencies.

The interaction between AI-driven audit tools and client trust has also been a key concern. Evidence indicates that AI-enabled audit services can positively influence trust when combined with auditors' professional expertise, as trust is not generated solely by technology but also by the perceived credibility of human involvement (Rawashdeh, 2024). Financial executives similarly show a cautious acceptance of AI in reporting and auditing, appreciating its efficiency but acknowledging the irreplaceable role of experienced professionals in interpreting outcomes (Estep et al., 2024). Together, these studies suggest that AI adoption does not diminish the importance of human auditors; instead, it highlights the need for advanced training and continuous upskilling to maintain credibility in client relationships.

Beyond immediate practice, the integration of AI is also driving anticipatory innovation within professional services. Audit firms are increasingly rethinking traditional structures and practices, adopting AI not just as a tool for efficiency but as a catalyst for broader organisational transformation (Goto, 2023). This shift highlights the need for human capital to evolve beyond technical competencies, embracing strategic agility to remain relevant in AI-augmented auditing environments. When combined, these studies demonstrate that the coexistence of AI and human auditors relies on developing adaptive competencies, safeguarding scepticism, and integrating innovation-oriented thinking into professional practice.

AI Adoption and Readiness in Audit Firms

Adoption decisions are commonly shaped by structured decision frameworks and by identifiable technical and organisational criteria. Research emphasises the usefulness of multi-criteria decision tools to guide adoption choices, with proposals that combine fuzzy-rough set theory and MRDM to prioritise alternatives under multiple perspectives (Hu et al., 2021). Exploratory fieldwork supports this orientation, showing that adoption drivers include perceived benefits, compatibility with existing processes, and maturity of AI tools (Seethamraju & Hecimovic, 2023). Studies additionally indicate that decision models must account for data quality and trust factors as central adoption enablers, and that formalised selection procedures reduce ambiguity when firms evaluate competing AI techniques (Hu et al., 2021, 2023; Seethamraju & Hecimovic, 2023).

Client digital transformation and internal IT expertise function as important moderators of adoption outcomes. Evidence from archival and survey studies suggests that client digitalisation raises the returns to auditors' AI investments, because digitally mature clients provide richer, more accessible data and thereby make AI tools more effective (Rahman & Ziru, 2023). When audit firms possess higher digital expertise, complementarity arises increased firm IT capacity attenuates audit risk and improves audit quality in AI-assisted engagements (Rahman et al., 2024; Rikhardsson et al., 2022). Small-firm contexts differ, since SME auditors report expectations of efficiency gains but face constraints from smaller data sets and lower resource availability, implying that client-firm fit matters strongly for successful AI uptake (Rahman et al., 2024; Rikhardsson et al., 2022)

Organisational structure and workforce implications are recurrent themes in adoption discussions. Evidence indicates that AI adoption is not merely a technical change but also a structural one, reshaping job content, skill demands, and centre-of-excellence arrangements within firms (Law & Shen, 2025). Field studies identify centralised service R&D or specialised AI teams as common organisational responses that help coordinate deployment and maintain quality control, while local offices often decide on deployment timing and scope (Kokina et al., 2025; Seethamraju & Hecimovic, 2023). The literature also reports that adoption can increase demand for soft skills and domain knowledge, shifting human capital requirements toward interpretation, judgment, and client communication rather than routine data processing (Kokina et al., 2025; Law & Shen, 2025; Seethamraju & Hecimovic, 2023).

Barriers and enablers coexist across technological, regulatory, and human-capital dimensions. Commonly reported barriers include concerns about data quality, lack of regulatory guidance, integration complexity, and limited internal capabilities for model governance (Kokina et al., 2025) (Hu et al., 2021). Studies recommend capacity-building programmes, clearer governance frameworks, and stepwise adoption roadmaps to mitigate these obstacles, especially for smaller firms that lack scale economies (Kokina et al., 2025; Rikhardsson et al., 2022).The combined evidence supports the view that successful adoption relies on aligning technical solutions with firm readiness, client characteristics, and governance arrangements rather than on technology capability alone (Hu et al., 2023; Law & Shen, 2025; Rahman et al., 2024).

AI and Audit Quality, Risk Assessment, and Reporting Outcomes

AI-enabled models are shown to reshape the measurement and management of audit risk. Studies that develop neural-network-based risk models report improved predictive accuracy compared to traditional approaches, especially in complex data environments (Niu et al., 2022). Deep learning frameworks also demonstrate the ability to detect patterns in financial statements that link directly to potential misstatements, enhancing reliability in audit risk assessment (Dai & Zhu, 2022). Evidence further supports that when risk assessment is AI-assisted, auditors can allocate resources more efficiently while maintaining scepticism, leading to better outcomes for stakeholders (Chen et al., 2022; Dai & Zhu, 2022; Niu et al., 2022)

Fee structures and audit effort estimation are also influenced by AI implementation. Neural network applications have been tested for their ability to estimate abnormal audit fees, indicating that AI-based models can detect overpricing or underpricing scenarios more accurately than traditional regression models (Choi et al., 2022). Such tools provide audit firms with more transparency when negotiating client contracts, improving both trust and efficiency. Complementary work on full-population auditing using machine learning demonstrates that when audit evidence is expanded beyond sampling, fee anomalies are more likely to be identified, strengthening independence and audit quality (Chen et al., 2022; Choi et al., 2022). AI applications also alter financial reporting outcomes by shaping disclosure quality and reporting tone. Evidence from emerging markets reveals that AI adoption in accounting disclosure influences tone management, with observable improvements in neutrality and consistency that are positively reflected in audit quality assessments (Muter et al., 2024). Parallel studies in Iraq show that AI integration into e-accounting programmes enhances report quality through timely detection of irregularities and more accurate financial information (Mohammed & Wahha, 2024). This suggests that AI-driven processes reduce bias in reporting and limit managerial discretion, thereby contributing to improved audit reliability (Chen et al., 2022; Mohammed & Wahha, 2024; Muter et al., 2024).

Evidence from different geographical settings confirms that AI strengthens both quality and efficiency outcomes in audit engagements. Case studies in Bangladesh highlight that AI contributes to better fraud detection, reduced error risk, and improved transparency in local audits (Arafat et al., 2025). Parallel evidence from China demonstrates that AI adoption by both audit firms and clients enhances audit efficiency while sustaining quality, pointing to complementary benefits when both parties integrate AI solutions (Rahman et al., 2024). Collectively, these studies underscore that the positive effects of AI adoption on audit outcomes are most visible when audit firms combine advanced modelling with supportive client digitalisation practices (Arafat et al., 2025; Muter et al., 2024; Rahman et al., 2024).

AI-Driven Audit Models and Methodologies

Recent work shows that machine learning and deep learning methods provide measurable gains in audit procedures, particularly in anomaly detection, risk scoring, and population-level testing. Studies comparing algorithmic approaches find that data-driven models outperform traditional heuristics for identifying irregularities in large-scale datasets. For instance, research on full-population auditing using machine learning reports higher detection coverage than sample-based approaches, indicating a shift in the feasible audit scope (Chen et al., 2022). Complementary investigations using neural-network architectures, such as BP networks and deep neural networks, report improved precision in audit risk estimation and abnormal fee detection relative to classic regression frameworks (Choi et al., 2022; Niu et al., 2022). Evidence from intelligent audit modelling also indicates that deep learning models can extract latent features from financial variables that correlate with audit outcomes, enabling more targeted substantive testing (Dai & Zhu, 2022).

Organizational research further highlights design considerations necessary for robust implementation. Comparative analysis of algorithm outputs shows sensitivity to feature selection, class imbalance, and training data representativeness, which in turn affects audit reliability (Chen et al., 2022; Choi et al., 2022; Niu et al., 2022). Hybrid approaches that combine rule-based governance with machine learning are proposed to mitigate opacity and to embed audit heuristics into model decision logic (Hu et al., 2023). Practical case findings stress that methodological transparency and post-model validation steps are critical for auditors to maintain professional scepticism when relying on model outputs (Chen et al., 2022; Dai & Zhu, 2022; Hu et al., 2023)

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Operational implications emphasise workflow redesign and evidence handling. Reports advocating full-population methods argue for reallocation of auditor effort from sampling toward exception investigation and model oversight, with documented improvements in coverage and potential reductions in undetected misstatements (Chen et al., 2022; Fedyk et al., 2022). However, comparative analyses caution about overreliance on algorithmic outputs without adequate model governance; empirical model errors or misspecification can produce false positives or negatives that influence audit opinions (Fedyk et al., 2022; Niu et al., 2022; Semenova et al., 2023). Taken together, these organizational studies suggest that technical performance gains are available but dependent on rigorous feature engineering, robust validation, and integration of governance layers to preserve audit judgment.

Governance, Ethics, and Auditability of AI

A clear theme across abstracts is the centrality of governance structures and ethical auditing to ensure AI tools produce trustworthy audit outcomes. Work on modernising national accounting and auditing systems argues that digital transformation must be accompanied by legal and institutional mechanisms to assure data integrity, traceability, and compliance (Shapovalova et al., 2023). Research into AI ethics auditing highlights that current practices emphasise technical risks such as bias and explainability, but often lack stakeholder involvement and measurable success metrics, which undermines audit credibility (Schiff et al., 2024). Studies focusing on bridging IT auditors with AI auditing specify the auditability measures and competencies that auditors must develop to effectively evaluate AI-driven processes (Li & Goel, 2025a). The collective message is that governance frameworks must combine technical controls with institutional responsibilities to sustain assurance quality (Li & Goel, 2025a; Schiff et al., 2024; Shapovalova et al., 2023)

Auditability and auditor readiness are recurrent practical concerns that shape adoption pathways. Foundational work proposes specific auditability measures, data lineage, model versioning, explainability logs—and links these measures to auditor competencies such as model interpretation and data governance oversight (Li & Goel, 2025a). Field-based findings document friction where firms implement AI rapidly but without commensurate internal control adjustments or audit trails, producing governance gaps that external and internal auditors must address (Li & Goel, 2025b; Schiff et al., 2024; Shapovalova et al., 2023). Recommendations emphasise phased adoption, clear allocation of oversight responsibilities, and training programmes to raise auditor readiness for model evaluation (Li & Goel, 2025b; Schiff et al., 2024; Shapovalova et al., 2023).

Regulatory and ethical considerations influence the perceived legitimacy of AI-assisted audits. Analyses indicate that the absence or immaturity of regulation increases uncertainty about acceptable assurance standards and may slow adoption; conversely, clearer regulatory guidance enables more consistent model governance and audit reporting (Schiff et al., 2024). The modernisation literature stresses harmonisation between technological standards (e.g., data formats, audit logging) and governance rules to support cross-jurisdictional comparability and audit trail robustness (Shapovalova et al., 2023). The synthesis implies that ethical auditing, auditability measures, skilled auditors, and regulatory clarity form an interdependent system required to translate AI capability into verified improvements in audit quality (Li & Goel, 2025b, 2025a; Schiff et al., 2024).

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Conclusion

This systematic literature review aimed to synthesize existing scholarly work on the impact of artificial intelligence and human capital on audit quality. The review was conducted using a structured PRISMA framework, analyzing articles published primarily between 2021 and 2025 from the Scopus and Web of Science databases. The study aimed to address key research questions regarding the evolving role of auditors, the determinants of AI adoption, its measurable impact on quality and efficiency, the efficacy of new audit methodologies, and the critical governance frameworks necessary for the ethical implementation of AI.

The analysis revealed several consistent themes. First, AI technologies demonstrably enhance audit quality by improving the accuracy and efficiency of procedures such as risk assessment, anomaly detection, and full-population testing. Second, the successful integration of these technologies is not merely a technical issue but is fundamentally dependent on human capital. The findings indicate that auditors must develop new competencies to oversee AI tools, maintain professional scepticism, and interpret complex algorithmic outputs. Third, adoption is influenced by a confluence of factors, including organisational readiness, client digital maturity, and the availability of structured decision-making frameworks. Finally, the review underscores that the benefits of AI are contingent upon robust governance mechanisms that ensure transparency, auditability, and ethical use.

This review contributes to the field by providing a comprehensive synthesis of previously fragmented research on the interconnected roles of technology and human expertise in auditing. It offers a novel thematic framework that categorises the literature into five core areas: competencies, adoption, outcomes, methodologies, and governance. This framework clarifies the multifaceted nature of AI integration, establishing that technological capability and human capital are not substitutes but complementary elements that jointly determine audit quality. The study thereby provides a consolidated knowledge base for researchers and theorists.

The synthesised evidence has significant practical implications. For audit firms, the findings underscore the importance of investing in continuous training programs to enhance auditors' AI-related skills and strategic judgment. For standard-setters and regulators, the review emphasises the urgent need to develop clear guidelines and governance standards for AI implementation in audit practice to ensure consistency, reliability, and ethical compliance. Furthermore, the identification of key adoption drivers and barriers provides a practical roadmap for firms of all sizes to strategize their AI implementation journeys effectively.

This review is subject to certain limitations. Its scope was restricted to articles in English from two major databases, potentially omitting relevant studies published in other languages or journals. The rapid evolution of AI technology also means that the literature is still emerging, and later developments may extend beyond the included publication timeframe. Based on the identified gaps, future research should prioritise longitudinal studies to measure the long-term impact of AI on audit quality, develop standardised metrics for auditing AI systems themselves, and empirically test the effectiveness of the proposed hybrid competency models and governance frameworks in various organisational contexts.

In conclusion, this systematic review highlights the crucial importance of a comprehensive approach to AI integration in auditing, one that strikes a balance between technological innovation and the development of human capital and robust governance. It confirms that the future of audit quality lies in the synergistic partnership between human expertise and artificial intelligence. As the field continues to evolve, such evidence-based synthesis is invaluable for advancing theoretical understanding, shaping effective practice, and guiding future empirical research in this transformative era for the auditing profession.

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