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ORIGINAL

Mapping the factors influencing artificial intelligence adoption in auditing: a bibliometric analysis

Mapeo de los factores que influyen en la adopción de la inteligencia artificial en la auditoría: un análisis bibliométrico

Lai Thi Thu Thuy[1]

[1]Institute of Accounting and Auditing, Thuongmai University, Hanoi. Vietnam.

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Corresponding author: Lai Thi Thu Thuy

ABSTRACT

Artificial intelligence has emerged as a decisive force in the auditing profession because it enhances automation, improves fraud detection, and strengthens professional judgment. However, the academic literature still lacks an integrated view of the factors that shape its adoption in auditing. This study addresses this gap by examining the intellectual structure and research trends on artificial intelligence adoption in auditing from 2016 to 2025 through a bibliometric approach. Data were obtained from the Dimensions database, and 210 English-language journal articles were retained after screening. The analysis employed text-based co-occurrence techniques to identify the main research themes and conceptual linkages. The results reveal five dominant lines of work: the transformation of internal and financial audits, the use of data analytics and digital tools, the adoption of new technologies and their effects on efficiency within audit firms, auditors' perceptions and behavioral responses, and the broader opportunities and challenges facing the auditing profession. These findings show a progression from conceptual discussions toward empirical examinations that consider organizational, ethical, and strategic implications. The study offers a consolidated overview of how artificial intelligence adoption has evolved in auditing and provides a reference point for future investigations seeking to promote responsible and sustainable technological integration in assurance practices.

Keywords: Artificial Intelligence; Bibliometric Analysis; Audit Profession; Digital Transformation; Technology Adoption; Auditor Perception.

RESUMEN

La inteligencia artificial se ha convertido en una fuerza decisiva en la profesión de auditoría porque aumenta la automatización, mejora la detección del fraude y fortalece el juicio profesional. No obstante, la literatura académica aún carece de una visión integrada de los factores que determinan su adopción en la auditoría. Este estudio aborda esta brecha mediante un examen de la estructura intelectual y las tendencias de investigación sobre la adopción de la inteligencia artificial en la auditoría entre 2016 y 2025, utilizando un enfoque bibliométrico. Los datos se obtuvieron de la base de datos Dimensions, y se seleccionaron 210 artículos en inglés tras el proceso de depuración. El análisis empleó técnicas de coocurrencia basadas en texto para identificar los principales temas de investigación y los vínculos conceptuales. Los resultados revelan cinco líneas de trabajo predominantes: la transformación de la auditoría interna y financiera, el uso de la analítica de datos y herramientas digitales, la adopción de nuevas tecnologías y su impacto en la eficiencia de las firmas de auditoría, las percepciones y respuestas de los auditores, y las oportunidades y desafíos que enfrenta la profesión de auditoría. Estos resultados muestran una transición desde discusiones conceptuales hacia estudios empíricos que consideran implicaciones organizacionales, éticas y estratégicas. El estudio ofrece una visión consolidada de la evolución de la adopción de la inteligencia artificial en la auditoría y constituye una referencia para futuras investigaciones orientadas a fomentar una integración tecnológica responsable y sostenible en las prácticas de aseguramiento.

Palabras clave: Inteligencia Artificial; Análisis Bibliométrico; Profesión de Auditoría; Transformación Digital; Adopción Tecnológica; Percepción Del Auditor.

INTRODUCTION

The auditing profession has experienced substantial changes over the past decade as artificial intelligence (AI) and related technologies such as automation, big data, and machine learning enter audit environments.[1,2,3] AI adoption in auditing refers to the use of intelligent systems that support auditors in performing tasks such as risk assessment, anomaly identification, evidence evaluation, and professional judgment. These technologies have progressed from early automated routines to advanced analytical applications capable of processing large datasets and revealing patterns that traditional procedures may not detect. This progression has increased expectations regarding audit efficiency, fraud detection, reporting quality, and the technological capabilities required of auditors.[4,5,6] From 2016 to 2025, academic interest in AI and auditing has grown significantly, reflecting both technological advancements and the broader movement toward digital transformation within professional service firms.[7,8,9] Interdisciplinary research has also emphasized how emerging technologies such as blockchain influence transparency, trust, and information integrity across financial systems,[10] reinforcing the convergence between AI-driven auditing and blockchain-enabled financial innovations.[11]

Despite this expansion of research, most prior studies have examined specific applications of AI—such as robotic process automation, audit data analytics, or their effects on audit quality[12,13] - rather than offering an integrated understanding of the factors that influence AI adoption in auditing. Although bibliometric and literature review studies exist in related accounting and information systems fields,[2,14,15,16] comprehensive mapping of the intellectual structure surrounding AI adoption in auditing remains limited. Existing reviews often present conceptual discussions or fragmented perspectives, leaving a gap in understanding how technological, organizational, and human factors jointly shape adoption in audit practices.[17]

Earlier research on digital auditing tools, including computer-assisted audit techniques and data analytics,[18,19] established foundational knowledge for explaining how digital technologies enter audit processes. Building on these developments, recent studies have evaluated multiple aspects of AI in auditing, including its implications for audit quality, fraud detection, and auditor decision-making.[3,4,20] Other research has examined organizational and behavioral determinants of technology adoption, drawing on frameworks such as the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) model.[13,21] However, these contributions often address isolated perspectives or narrow contexts, which limits the ability to understand how AI adoption progresses across diverse auditing settings. Although bibliometric analyses exist in accounting and information systems[2,15,16] a systematic and consolidated mapping dedicated specifically to AI adoption in auditing is still absent.

To address this gap, the present study examines the intellectual foundations, thematic developments, and key factors that characterize AI adoption in auditing from 2016 to 2025. The study clarifies how the field has evolved, identifies dominant research directions, and highlights influential scholarly contributions. These insights are intended to support a clearer understanding of technological integration within the auditing profession and to inform future academic inquiry in this emerging domain.

METHOD

Type of study

This research is a quantitative, non-experimental, descriptive study based on bibliometric and network analysis. The study does not involve human subjects or interventions; instead, it analyzes scientific publications to map the intellectual structure and thematic development of AI adoption in auditing.

Universe and sample

The universe of this study consists of academic publications related to the use and adoption of AI within the auditing discipline. To construct the sample, bibliometric data were retrieved from the Dimensions database, which provides broad coverage of peer-reviewed research and updated citation information across disciplines. This database was selected because it offers wider inclusiveness compared with traditional sources such as Scopus and Web of Science, making it suitable for emerging and interdisciplinary topics.[16,22]

To ensure relevance to the research objectives, the search focused on studies examining the use and adoption of AI within the auditing discipline. The search query combined keywords related to AI technologies, adoption behavior, and auditing contexts, and was applied to the title and abstract fields. The final query was as follows:

("artificial intelligence" OR "AI" OR "machine learning" OR "data analytics") AND ("adoption" OR "acceptance" OR "implementation" OR "use" OR "integration") AND ("financial audit" OR "financial auditor" OR "auditing profession" OR "external audit" OR "internal audit" OR "audit firm" OR "accounting firm" OR "assurance").

The search was limited to journal articles classified under the 3501 Accounting, Auditing, and Accountability field according to the ANZSRC 2020 classification, and published between 2016 and 2025. This process identified 313 records.

A manual data-cleaning process was then conducted to ensure accuracy and relevance. Non-English publications, studies outside the auditing domain (e.g., management information systems or general AI in accounting), and duplicate records were excluded. After refinement, 210 articles remained for analysis. These records formed the final dataset used for descriptive and network-based bibliometric analyses.

The data screening and selection process followed established procedures[23,24] and the recommended practices for transparent bibliometric reporting.[17,25,26] Figure 1 presents the flowchart that summarizes the identification, screening, exclusion, and inclusion stages applied to refine the final dataset.

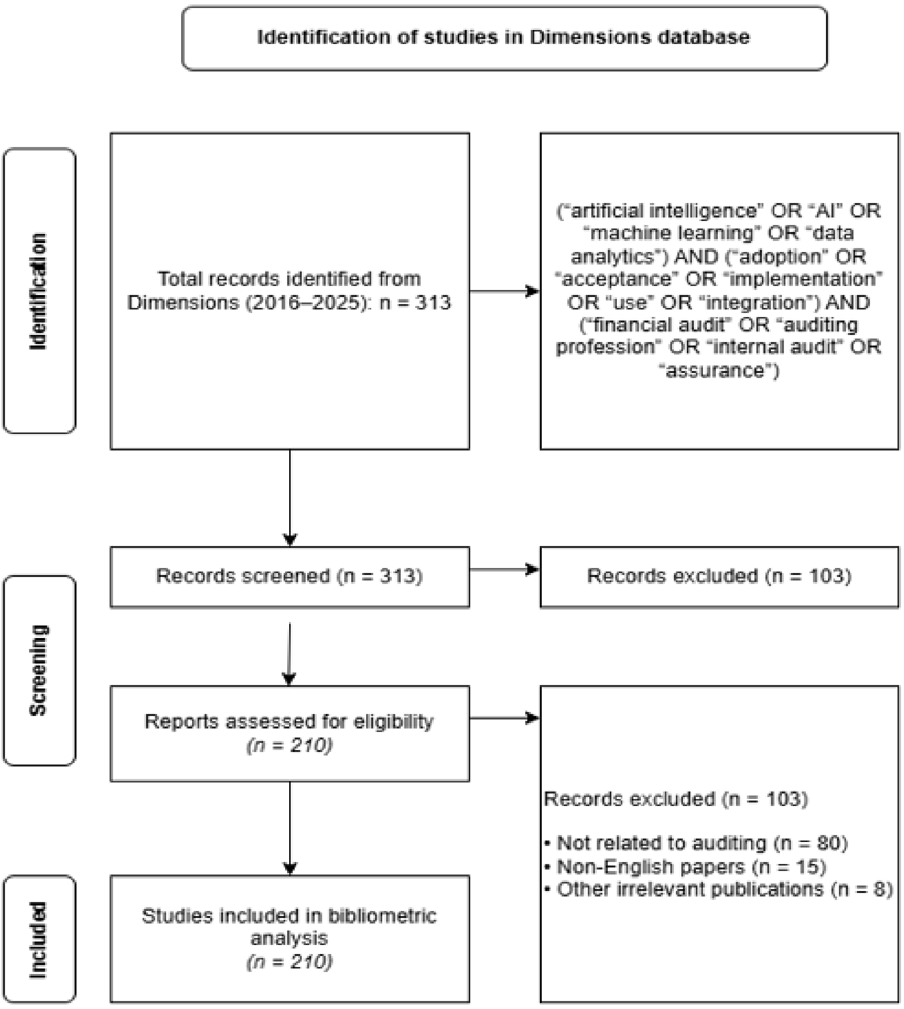

Figure 1. Study identification and screening flowchart[23,24]

Variables

The analysis focused on bibliometric variables relevant to mapping studies, including:

Publication trends (distribution of articles by year).

Citation impact (citation counts obtained from Dimensions).

Textual terms extracted from article titles, used to generate co-occurrence networks and thematic clusters in VOSviewer.

Data collection and processing

The dataset retrieved from Dimensions was exported in CSV format and manually cleaned using Microsoft Excel. The cleaning process included removing inconsistencies, standardizing titles, deleting non-relevant fields, and preparing the final file for import into VOSviewer. No additional transformation or statistical preprocessing was applied beyond what was required for the co-occurrence and clustering analysis.

Data analysis

The bibliometric and text analyses were conducted to identify the intellectual structure and emerging themes of research on AI adoption in auditing. Following the methodological guidelines of Donthu et al.(15), Aria and Cuccurullo(27), and Zupic and Čater(22), both descriptive bibliometric indicators and network-based analyses were applied to examine research trends, thematic structures, and intellectual linkages within the field.

To provide a structured and transparent analytical process, the bibliometric indicators were first processed manually using Excel. This step included verifying publication years, journals, authorship information, country contributions, and citation counts to ensure consistency and remove formatting errors.

Text data were extracted from the title field of the 210 selected publications and analyzed using VOSviewer version 1.6.20.(25,26) The analysis employed binary counting, where each keyword occurrence was counted once per document to avoid bias toward longer titles or repetitive terminology. A minimum occurrence threshold of four was established to ensure that only keywords with sufficient relevance were included in the co-occurrence network.

A keyword co-occurrence analysis was then performed to visualize conceptual relationships among key research terms. Each node represented a keyword, while the links indicated co-occurrence relationships within the same publication. The resulting clusters reflected groups of interrelated topics, revealing the major research themes and conceptual linkages shaping AI-related auditing scholarship.

The generated co-occurrence clusters were then interpreted and grouped into broader thematic categories, allowing the study to identify dominant research directions and conceptual patterns within the field. This interpretative step ensured that the analysis not only visualised term relationships but also produced structured thematic insights that reflect how AI adoption has been examined in auditing research. All visualizations and bibliometric metrics were generated directly through VOSviewer, ensuring methodological consistency, analytical transparency, and reproducibility.(17)

Ethical standards

This study relies exclusively on secondary bibliographic data from publicly accessible scientific databases. No human subjects were involved, and no ethical approval was required. All sources are cited according to the journal's referencing standards.

RESULTS

Descriptive analysis

The descriptive bibliometric analysis provides an overview of the publication landscape on AI and auditing between 2016 and 2025. As illustrated in figure 2, research output on AI and auditing has grown steadily since 2016. The number of publications remained low before 2019 but rose sharply from 2020 onward, reaching a peak of 83 papers in 2025.

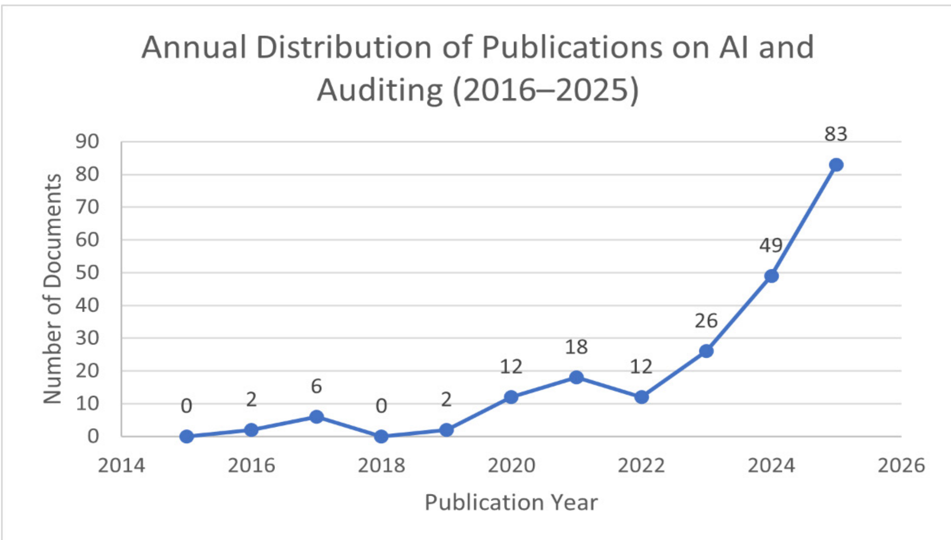

Figure 2. Publication trend on AI in auditing (2016–2025)

Table 1 presents the ten most frequently cited papers in the dataset. The most cited works include Kokina and Davenport[3] and Han et al.[2], followed by studies such as Issa et al, Fedyk et al, and Hasan[4,20,28]. These publications have received the highest citation counts within the sample period and represent the studies most referenced in the academic literature on AI and auditing.

Table 1. Most cited authors and studies on AI in auditing (2016–2025)

No.	Title	Journal	Year	Authors	Times cited	Key contribution
1	The Emergence of Artificial Intelligence: How Automation is Changing Auditing	Journal of Emerging Technologies in Accounting	2017	Kokina & Davenpor[3]	492	Overview of AI applications in auditing; impact on audit process and human auditors
2	Accounting and auditing with blockchain technology and artificial intelligence: A literature review	International Journal of Accounting Information Systems	2023	Han et al.[2]	397	Review of AI and blockchain integration in auditing; transparency and trust issues
3	Research Ideas for Artificial Intelligence in Auditing	Journal of Emerging Technologies in Accounting	2016	Issa et al.[20]	333	Proposes future research directions for AI in auditing and assurance
4	Is artificial intelligence improving the audit process?	Review of Accounting Studies	2022	Fedyk et al.[4]	262	Empirical evidence on AI investments and audit quality
5	Artificial Intelligence (AI) in Accounting & Auditing: A Literature Review	Open Journal of Business and Management	2022	Hasan[28]	202	Narrative review of AI adoption and challenges in auditing profession
6	Explaining the (non-) adoption of advanced data analytics in auditing	International Journal of Accounting Information Systems	2021	Krieger et al.[21]	113	Process theory of data-analytics adoption in audit firms
7	Learning from Machine Learning in Accounting and Assurance	Journal of Emerging Technologies in Accounting	2020	Cho et al.[29]	98	Editorial highlighting ML applications and ethical implications
8	The Use of Artificial Intelligence and Audit Quality: An Analysis from External Auditors in the UAE	Journal of Risk and Financial Management	2022	Noordin et al.[30]	97	Survey on auditors' perceptions of AI and audit quality
9	Organizational and environmental influences in the adoption of CAATTs by audit firms in Malaysia	International Journal of Accounting Information Systems	2020	Siew et al.[18]	95	Examines TOE factors affecting CAATTs adoption
10	An Exploratory Study into the Use of Audit Data Analytics on Audit Engagements	Accounting Horizons	2020	Eilifsen et al.[12]	87	Explores practical use of ADA across audit phases

Co-occurrence network

The co-occurrence network visualization (figure 3) illustrates the relationships among keywords extracted from the titles of 210 selected articles. Using *VOSviewer*,[25,26] five major thematic clusters were identified, representing the main research directions on AI in auditing.

The first cluster (red) focuses on internal and financial audit transformation, highlighting how AI, automation, and analytics are reshaping traditional audit processes. Keywords such as internal audit, financial audit, fraud detection, and integration suggest that researchers have emphasized the role of AI in enhancing accuracy, preventing fraud, and improving assurance quality.

The second cluster (blue) centers on data analytics and digital transformation. Terms like data analytic, digital transformation, literature review, and insight indicate growing scholarly attention to the integration of analytics in auditing and its contribution to evidence-based decision-making. This stream often includes bibliometric and conceptual reviews examining how digital technologies facilitate knowledge creation and methodological innovation in auditing.

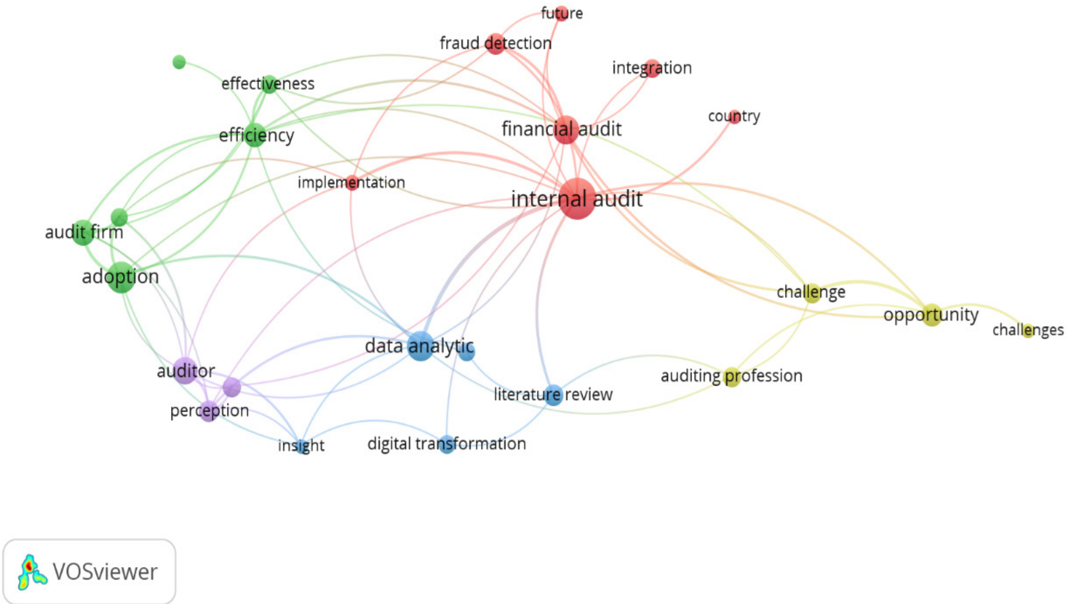

Figure 3. Term co-occurrence network visualization(25,26)

The third cluster (green) relates to adoption and efficiency in audit firms. It comprises keywords such as adoption, audit firm, efficiency, and effectiveness, reflecting studies that investigate the determinants and outcomes of AI adoption. These works commonly explore how organizational readiness, firm size, and technological capability influence audit performance and operational improvement.

The fourth cluster (purple) highlights auditor perception. It contains the keywords auditor and perception, representing research exploring how auditors perceive and respond to technological changes in the audit process, particularly regarding the application of AI and data analytics.

The fifth cluster (yellow) addresses opportunities and challenges in the auditing profession. Keywords such as opportunity, challenge, and auditing profession capture the broader discussions on strategic, ethical, and regulatory implications of AI integration. These studies explore barriers to adoption and propose policy and professional frameworks for sustainable technological implementation.

Taken together, the five clusters provide a comprehensive picture of how the literature conceptualizes AI in auditing-from technological transformation and organizational adoption to behavioral and professional implications. The strong interconnections among clusters demonstrate that AI research in auditing has become increasingly interdisciplinary, bridging insights from technology management, behavioral accounting, and audit practice.

The overlay visualization (figure 4) maps the temporal evolution of keywords, with colors indicating each term's average publication year (blue/purple = earlier; yellow = more recent). The earliest stream (2022–early 2023, blue-purple) concentrates on data analytic, perception, and country, marking foundational, exploratory work. A mid-phase around 2023 (cyan-green) centers on internal audit, auditor, adoption, audit firm, and auditing profession, reflecting the diffusion of digital technologies across organizations and professional roles. The most recent focus (late 2023–2024, yellow) shifts to execution and outcomes, emphasizing implementation, digital transformation, efficiency, effectiveness, integration, opportunity, challenge, as well as financial audit and literature review.

Overall, the trajectory illustrates a progressive deepening of scholarly inquiry within the auditing domain. Early studies emphasized the exploratory use of data analytics to support internal audit activities, focusing on how technological capabilities could enhance auditors' judgment, insight, and perception. Subsequent research shifted toward organizational adoption, examining how audit firms and professionals integrate digital tools into existing assurance processes to improve audit efficiency and effectiveness. In the most recent stage, attention has moved toward large-scale implementation and performance evaluation, with studies assessing how AI, automation, and data-driven systems reshape audit methodologies, redefine professional competencies, and influence the overall governance and assurance landscape. This evolution reflects the auditing profession's ongoing transformation-from conceptual and experimental applications of AI to strategic integration aimed at strengthening audit quality, risk management, and organizational accountability.

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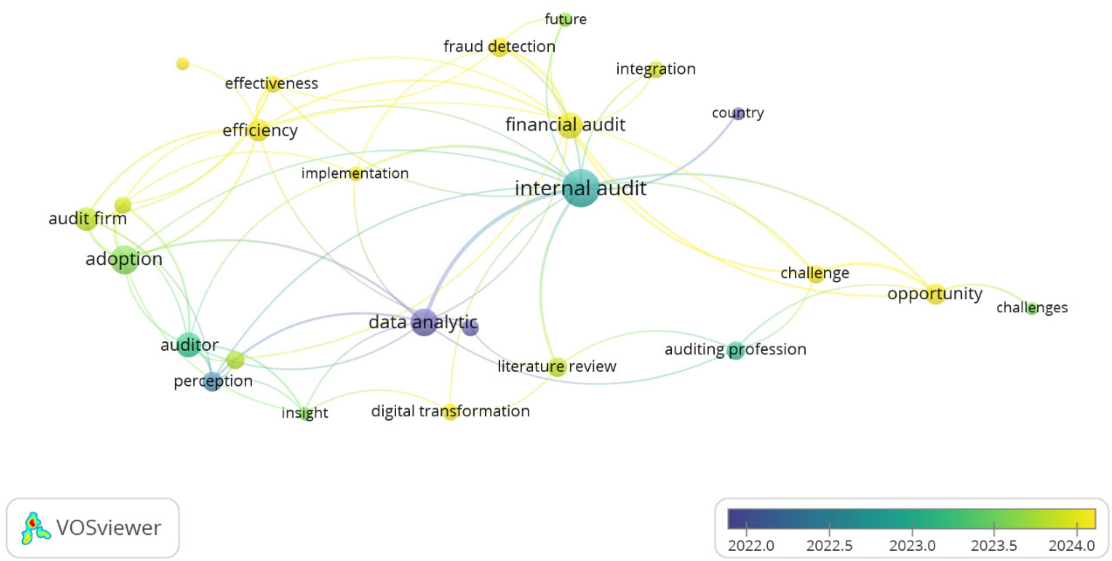

Figure 4. Overlay visualization of keyword co-occurrence[25,26]

DISCUSSION

Insights from the descriptive analysis

The descriptive results provide contextual evidence on how AI-related auditing research has evolved over the past decade. The steady increase in publications after 2020 indicates that academic interest has expanded in parallel with the digital transformation of audit practice. Highly cited studies [2,3,20] show that the intellectual foundations of the field are shaped by early conceptual discussions on automation and later strengthened by empirical evidence on audit quality, adoption behaviors, and data-driven decision-making. Country- and journal-level distributions further reveal that leading contributions originate mainly from technologically advanced audit markets, suggesting that institutional capacity and regulatory environments play an important role in shaping the development of AI research in auditing.

Insights from the co-occurrence network

The keyword co-occurrence network reveals five interrelated thematic clusters, indicating that AI-related auditing research has developed along multiple intellectual directions rather than a single dominant theme. The presence of distinct clusters highlights the field's conceptual diversity, spanning adoption behavior, technological capabilities, audit quality implications, organizational change, and emerging digital tools. These clusters collectively illustrate the core themes shaping the evolution of AI adoption in auditing and provide the foundation for the thematic interpretation that follows.

Cluster 1 – Internal and financial audit transformation

This cluster reflects the transformation of internal and financial audit activities driven by automation, analytics, and intelligent tools. The literature shows a progressive shift from conceptual discussions to practical evaluations of AI-enabled audit processes. Early studies emphasized conceptual integration and the potential of AI to formalize audit tasks[20,31] whereas later empirical work demonstrated improvements in fraud detection, reliability, and assurance quality.[4,32]

Recent contributions also highlight persistent challenges, such as data integrity and model transparency, which influence how audit functions operationalize AI.[33,34] Similar concerns appear in research on internal audit automation[35] showing that implementation outcomes vary depending on governance culture, technological readiness, and organizational maturity.[36,37,38]

Taken together, this cluster suggests that AI adoption in internal and financial auditing is progressing, but its impact remains conditional on firms' infrastructural and governance capabilities. Compared with earlier studies, which tended to emphasize technological potential, recent evidence places stronger weight on organizational and contextual factors.

Cluster 2 – Data analytics and digital transformation

The second cluster underscores the central role of audit data analytics (ADA) in enabling evidence-based

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auditing and continuous assurance. Prior studies demonstrated how ADA enhances sampling, evidence collection, and risk assessment.[12,21] Bibliometric reviews reinforce this dual technological and methodological role of analytics in reshaping audit practices.[2,28]

Adoption disparities, however, remain visible across firm sizes and jurisdictions.[39,40] Broader reviews also position AI and robotic process automation as complementary innovations contributing to a more integrated digital audit environment.[41] More recent studies further emphasize how cloud computing, automation, and generative AI reshape auditors' analytical capabilities and decision-support functions.[42,43,44,45]

Overall, this cluster indicates that digital transformation is unfolding unevenly. While large and technologically advanced firms benefit most, smaller practices still face adoption barriers—a finding consistent with global ADA studies.[12,45]

Cluster 3 – Adoption and efficiency in audit firms

This cluster examines determinants of AI adoption at the firm level and the resulting implications for audit efficiency. Empirical work shows that organizational readiness, firm size, and technological capability influence the speed and quality of implementation.[13,21] These findings align with prior research documenting productivity gains, improved risk assessment, and enhanced client service resulting from AI use,[46,47] while also noting persistent challenges in aligning technology with human resource development.[48,49] Complementary analyses show that adoption outcomes are moderated by firm culture, competitive pressures, and governance adaptability.[5,37,50,51] This implies that technology alone is insufficient; successful AI initiatives depend on how organizations align their structures and strategies. Based on the combined evidence, this cluster illustrates that AI adoption is both a technological and managerial process requiring sustained investment in skills, systems, and change management.

Cluster 4 – Auditor and auditor perception

The fourth cluster centers on auditors' perceptions, trust, and behavioral responses toward AI-assisted auditing. Research shows that beliefs about usefulness, perceived control, and task complexity shape willingness to use AI tools.[30,52] Studies applying the TAM framework emphasize that technology adoption is tightly linked to auditors' ethical concerns, autonomy, and professional skepticism.[53,54]

With the emergence of generative AI, newer work stresses the need for auditor autonomy and ethical reasoning when integrating such tools into IT audit support.[55] Empirical findings further indicate that experience, training, and skepticism significantly affect trust in AI-assisted decisions, reinforcing the need for ethical frameworks and capability building.[56,57,58,59] Taken together, this cluster demonstrates that behavioral and cognitive dimensions remain central to AI adoption—an aspect that complements, rather than duplicates, the technological and organizational insights from prior clusters.

Cluster 5 – Opportunities and challenges in the auditing profession

The fifth cluster highlights broader strategic, ethical, and regulatory implications. Scholars note that AI can enhance audit reliability and fraud detection, but also introduces issues related to transparency, accountability, and regulatory oversight.[60,61,62] Earlier conceptual contributions, such as Imane[57], further emphasized the ethical dilemmas arising from algorithmic decision-making, explaining why institutional readiness and governance safeguards are essential when integrating AI into audit practice.

Recent studies also underline the need for updated audit standards, reskilling initiatives, and clearer regulatory frameworks to ensure responsible adoption, particularly as AI grows more embedded in judgment-intensive tasks.[8,63] Complementary evidence highlights the increasing relevance of cloud-based audit environments, cross-technology integration (AI–Big Data–Blockchain), and institutional governance mechanisms that strengthen audit accountability and transparency.[11,64,65] Reviews on blockchain-based assurance also illustrate how integrative frameworks can help synthesize fragmented research fields, offering directions for future AI-in-auditing syntheses.[10] This cluster underscores that AI adoption is not solely a technological shift but a structural transformation requiring coordinated regulatory, ethical, and institutional support.

Overall synthesis and author assessment

Across the five clusters, the findings show that auditing research has moved steadily from early conceptual discussions of automation toward more nuanced examinations of implementation conditions, behavioral influences, and governance implications. Taken together, these patterns indicate that AI adoption in auditing is evolving through three interconnected trajectories. The first reflects a process of technological modernization, where analytics, automation, and intelligent tools are increasingly embedded in audit procedures to enhance evidence quality and efficiency. The second involves organizational adaptation, as audit firms redesign workflows, invest in training, and strengthen governance structures to support the integration of digital technologies. The third concerns professional and ethical recalibration, with auditors developing new competencies while responding to emerging issues related to autonomy, trust, accountability, and ethical judgment.

When compared with earlier bibliometric studies,[1,2,14] this analysis reveals a stronger emphasis on governance, ethics, and cross-technology integration, indicating that the research agenda is expanding beyond the narrow focus on technological adoption. These synthesized insights not only clarify how AI is reshaping contemporary audit practice but also highlight important gaps that remain underexplored. In particular, future research would benefit from deeper investigation into causal relationships, the dynamics of auditor–AI interaction, and the regulatory responses required to ensure transparency and accountability in increasingly automated audit environments.

CONCLUSIONS

This study set out to examine the intellectual structure and thematic evolution of research on AI adoption in auditing from 2016 to 2025. By synthesizing the patterns observed across the literature, the analysis clarifies how the field has progressed and where it is heading. The findings demonstrate that AI adoption in auditing is no longer conceptualized merely as the introduction of advanced technologies, but rather as a multidimensional transformation that intersects with organizational capabilities, professional judgment, regulatory expectations, and broader institutional developments. This reflects a clear shift from early technologically driven narratives toward more holistic considerations of governance, ethics, and auditor competence in digital audit environments.

In addressing its objective, the study contributes theoretically by offering an integrated view of the knowledge base surrounding AI in auditing and by identifying the main thematic streams that shape current scholarly discourse. Practically, the synthesis highlights the strategic and regulatory implications of AI adoption, underscoring the need for capacity building, updated professional standards, and responsible innovation to maintain audit quality and protect the public interest.

Like other bibliometric research, the study is limited by its dependence on published journal articles, which may omit relevant insights from grey literature or non-English sources. Future research should complement bibliometric evidence with qualitative or mixed-method designs to deepen understanding of how auditors interact with AI, how regulatory frameworks can adapt, and how emerging technologies—such as blockchain-enabled assurance and explainable AI—may redefine the boundaries of audit practice.

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Project management: Lai Thi Thu Thuy.
*Resource*s: Lai Thi Thu Thuy.
Software: Lai Thi Thu Thuy.
Supervision: Lai Thi Thu Thuy.
Validation: Lai Thi Thu Thuy.
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