

Artificial Intelligence, Audit and Fraud Risk Management: A Bibliometric Analysis Review

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Abstract. *Artificial intelligence (AI) has evolved rapidly in recent years and has steadily become part of many aspects of life, including the field of audit and fraud risk management. Because of these developments, researchers have started to show a higher interest in the way AI can support auditors in identifying, assessing and reducing both audit and fraud-related risks. This paper presents a bibliometric study focused on the relationship of AI, auditing and fraud detection. The main objective of our study is to examine whether the existing literature identifies a clear connection, from an audit perspective, between the use of AI technologies and the way fraud is detected. To achieve this objective, the paper includes a bibliometric analysis of articles published in the ScienceDirect database over a period of almost three decades, more specifically from 1998 to 2025. Our analysis aims to identify the main research directions, the most frequent topics discussed by researchers and the extent to which AI tools are considered useful in fraud detection activities within auditing. The findings also point to several research gaps and underline the need for further investigation regarding the integration of AI into auditing practices. Particular attention should be given to the standardization of AI applications and to the development of auditors' competencies required for the effective use of these existing technologies. Given the continuous technological changes shaping the modern business environment, further research on AI applications in auditing remains highly relevant.*

Keywords: Artificial Intelligence (AI), Audit risk, Fraud detection, Literature review, ScienceDirect database, Bibliometric review.

Introduction

Over the last decade, the auditing profession has changed substantially, due to the rapid progression of artificial intelligence (AI) technologies. This evolution is altering not only the way in which auditors detect fraud, but also the way they perform audit engagements. On one hand, AI tools provide the opportunity to enhance efficiency, automate repetitive tasks and reduce human error. On the other hand, if not properly managed, these technologies can generate additional work and even produce unreliable outcomes.

This dual role creates an important challenge for auditors. Even if AI can assist the professionals in handling complex analysis and a large volume of information, human supervision remains essential. As a result, auditors nowadays should develop the skills necessary to use AI tools effectively, to critically interpret system-generated outputs and also to ensure that AI technologies support rather than compromise audit quality.

Recent developments in machine learning and natural language processing have significantly expanded auditors' capabilities. By improving risk assessment and anomaly detection, AI-empowered accounting information systems increase significantly auditing and fraud exposure (Qatawneh, 2024). Recent research studies also show that advanced AI integration can help control corporate financial fraud by strengthening internal controls and boosting information transparency (Yin et al., 2025). In addition, studies focusing on deep learning approaches have concluded that when it comes to fraud detection patterns, machine learning frameworks are effective and can also highlight challenges like data imbalance and privacy compliance (Chen et al., 2025). In comparison

to conventional methods, other studies have developed probabilistic machine learning models that integrate multiple sources of financial and non-financial information, demonstrating enhanced detection performance and greater interpretability (Fu et al., 2025).

Despite all the advantages that AI integration brings to the audit and fraud detection field, it also introduces new risks. Challenges such as algorithmic bias, limited model transparency, data quality questions and dependency on automated systems are usually recognized as factors that may weaken auditors' professional judgment and diminish audit value. To support previous empirical results, recent studies centering AI adaptation in audit have identified significant ethical and governance risks, such as fairness, accountability and privacy concerns. As a result, they also proposed remedies such as algorithmic testing and implementing ethical precautions when it comes to system design (Murikah et al., 2024). These findings emphasize the need for auditors to critically judge AI outputs and uphold accountability in order to maintain credibility and reliability of the audit missions.

Given the rapid evolution of technology, research on the use of AI in auditing and fraud detection has also grown significantly in recent years, covering everything from conceptual frameworks to experimental and empirical studies across accounting, auditing and information systems (Raisch & Krakowski, 2021). Despite this growth, the literature remains somewhat fragmented. Existing studies present inconsistent definitions of AI, approaches to understanding fraud risk vary and there is limited to no integration between traditional auditing approaches and technological advances. While some studies emphasize the clear benefits of adopting AI, such as more accurate fraud detection, greater cost efficiency and the ability to provide real-time assurance (Kokina et al., 2016; Perols et al., 2011), others focus on the challenges, including ethical concerns, regulatory gaps and the changing role of human judgment in audits supported by AI (Moffitt et al., 2018).

Starting from the literature and following the recommendations of Zupic & Carter (2015), this study aims to answer the following research questions:

RQ1: What are the research trends regarding the AI evolution in the context of audit and fraud detection?

RQ2: Which journals and authors are the most influential in the context of AI, fraud and auditing?

RQ3: What are the main themes explored in the literature and how have they evolved over time?

Building on these gaps, our study uses a bibliometric approach to thoroughly map the literature on AI applications within audit practices like risk assessment and fraud detection. The analysis was conducted using articles from the ScienceDirect database that met predefined inclusion and quality criteria. After screening, a final dataset of 829 research and review articles was selected, covering key contributions across business, management, accounting, economics and subsequently finance. We acknowledge that even if the ScienceDirect database primarily hosts Elsevier publications, it also provides sufficient coverage of high-quality peer-reviewed journals, conference papers and reviews in accounting, auditing, management and information systems, which are suitable for conducting keyword-based bibliometric analysis.

The structure of this article is as follows. Section 2 explores the main research trends and growing academic interest in artificial intelligence technologies and fraud detection within the auditing domain. Section 3 describes the bibliometric mapping approach by outlining the research design, the process of data collection and the use of analytical methods. In section 4 we discuss our findings and explore their implications for both academic research and professional practice. Finally, Section 5 concludes the study by highlighting its originality, while focusing on the research gaps and acknowledging its limitations.

Literature Review

Artificial intelligence (AI) in auditing has rapidly developed into a revolutionary tool enabling auditors to process large datasets and automate repetitive procedures. It also detects anomalies with more precision than traditional methods (Permata Suyono et al., 2025; Han et al., 2023).

Early studies argue that the increasing digitization of business processes has made traditional audit approaches insufficient, creating the need to use advanced analytics and AI-driven tools to address the challenges associated with the digital transformation (Vasarhelyi et al., 2015). Machine learning, robotic process automation (RPA) and natural language processing (NLP) are among the most widely applied technologies, supporting activities such as fraud detection, continuous auditing and real-time risk analysis (Kokina & Davenport, 2017; Fedyk et al., 2022; Vasarhelyi et al., 2015).

Recent research highlights the growing impact of artificial intelligence on auditing, fraud detection and financial fraud prevention. According to Qatawneh (2024), AI's role within accounting information systems was shown to significantly enhance auditing quality and fraud detection, with NLP further strengthening these effects by supporting systems in interpreting unstructured text such as reports or narratives. Furthermore, Sun et al. (2025) found that AI technologies significantly reduce both the likelihood and severity of corporate financial fraud. By using machine learning and text analysis on data from Chinese listed companies, the 2025 study shows that AI improves information transparency and strengthens internal control systems, which consequently reduces fraud.

Overall, these studies illustrate how AI not only supports auditors in processing large volumes of data and detecting anomalies but also plays a preventive role at the corporate level by reducing fraud occurrence. This highlights the growing and dual role of AI in both audit practice and corporate governance.

The next major finding indicates that AI adoption in audit processes can also enhance audit quality by reducing financial restatements, improving anomaly detection while lowering audit fees through efficiency gains (Fedyk et al., 2022; Yang, 2025). Additionally, AI-enabled continuous auditing models allow auditors to shift from periodic, sample-based testing toward full-population analysis, which subsequently can increase the assurance levels (Brown-Liburd et al., 2015).

Previous bibliometric studies further highlight that AI adoption is particularly prominent in external and internal auditing contexts, where predictive analytics and pattern recognition replace manual sampling and rule-based testing (Permata Suyono et al., 2025; Sari, 2025; Issa et al. 2016).

While these modern tools bring significant benefits, they also introduce new categories of risks that challenge traditional audit methods. In their study, Della Valle and Evangelista (2025) emphasize that AI systems may produce incorrect outputs due to biased training data, poor model generalization, lack of explainability, or incorrect validation. Munoko et al. (2020) argue that too much reliance on automated programs may weaken auditors' professional scepticism. Furthermore, "black box" AI models reduce transparency, making it difficult for auditors to justify their conclusions to regulators and stakeholders (Vasarhelyi et al., 2015; IAASB, 2023).

Academics also identify organizational and technological risks associated with AI-enabled audits, including cybersecurity vulnerabilities, system integration failures and insufficient governance frameworks (Kroon et al., 2021). In risk assessment contexts, AI enhances detection capabilities but may also include systematic errors when automated scoring models are poorly regulated or ineffectively supervised (Yang, 2025; Wassie & Lakatos, 2024). These concerns highlight the need for auditors to maintain strong human oversight and validation procedures when implementing AI tools.

One of the focal points when it comes to adopting AI is ethical and governance challenges. Sari (2025) finds that auditors' ability to adapt to new technologies, organizational culture and professional competence significantly influence the efficiency of AI implementation. Too much reliance on AI systems may weaken accountability, reduce professional judgment and shift responsibility away from auditors toward technology providers (Al-Qudah et al., 2025; Brown-Liburd et al., 2015). Regulatory bodies have similarly signalled that AI should support, rather than replace, auditor judgment, particularly in high-risk and fraud-sensitive engagements (PCAOB, 2024).

According to Della Valle and Evangelista (2025) robust ethical frameworks, clearly explained mechanisms and well-defined accountability structures are essential to ensure that the use of AI is done responsibly in the domain. Han et al. (2023) further highlight that auditors must understand AI limitations, including built-in biases and ethical risks, especially when it comes to applying AI in fraud detection or client risk evaluation. The absence of standardized global guidance on AI governance in auditing continues to create inconsistencies across firms and authorities (IAASB, 2023; Kroon et al., 2021).

Despite growing academic attention, research on AI in auditing remains conceptually fragmented and is limited in terms of empirical evidence. Existing studies often rely on cross-sectional designs, providing reduced insight into how specific AI tools influence audit quality over time and across different institutional contexts (Munoko et al., 2020; Permata Suyono et al., 2025). Moreover, the implications of AI adoption for auditor competencies, professional scepticism and ethical responsibility remain underexplored (Al-Qudah et al., 2025; Yang, 2025).

Research Methodology

This study adopts a bibliometric research design to methodically analyze the academic literature on artificial intelligence in auditing and fraud detection. The bibliometrics provide a quantitative approach for examining publication trends, identifying influential contributions and mapping how the structure of a research field has evolved (Donthu et al., 2021).

The data collection process was conducted in December 2025 using the ScienceDirect database. Although Scopus was initially considered due to its broader coverage, access limitations required the use of the ScienceDirect database. Even if it primarily includes Elsevier publications, which are generally of high quality, we acknowledge that the database chosen represents a limited subset of the overall literature and should be considered when interpreting the results.

The search strategy used combinations of the keywords "AI," "audit" and "fraud," applied to titles, abstracts, and keywords. The time frame was restricted to publications between 1998 and 2025, as the first relevant article in the database appeared in 1998. The initial search generated 2,695 documents. After applying the inclusion criteria, such as limiting results to research and review articles written in English and relevant to the audit field, the dataset was reduced to 2,106 papers. A further screening process based on abstract relevance resulted in a final sample of 829 publications.

The selected data were exported and analyzed using VOSviewer software, a tool that helps construct bibliometric networks, including keyword co-occurrence, publication trends and co-authorship designs. The analysis aims to identify dominant themes, collaboration structures and emerging research directions within the field.

Results and Discussion

The inclusion and exclusion criteria, together with the time frame chosen, document types and language restrictions are summarized in Table 1. This provides a transparent overview of the

screening process, showing how the initial search results were polished in order to ensure the relevance of the final dataset.

Table 1. Search criteria and results obtained

Search criteria	Result
Key words	“AI” & “Audit” & “Fraud”
Period	1998-2025
Area of interest	Accounting, Business, Economics, Finance, Econometrics
Document type	Review and research articles
Language	English
No. of documents before filtering	2,695
No. of documents after Filtering	829

Source: Authors’ own research results/contribution.

Starting from the research question *RQ1: What are the research trends regarding AI evolution in the context of audit and fraud detection?*, a performance analysis has been carried out to identify the evolution of academic interest at the intersection of artificial intelligence, auditing and fraud. The results presented in Figure 1 display that research activity remained limited between 1998 and 2014, with only a small number of publications each year. The evidence indicates that this period represents the early and experimental stage of AI adoption in auditing research.

Going forward, we observe that there is a clear ascending trend with a steady increase in publications between 2016 and 2022. This growth overlaps with the rising recognition and acknowledgement of the potential of AI technologies to improve audit processes and fraud detection. After 2022, the trend accelerates significantly, reaching its peak in 2025. This sudden increase aligns with the rapid technological developments over the last few years, including their integration into business processes and auditing practices.

Overall, the ScienceDirect database analysis shows that AI-related research in auditing and fraud has shifted from a niche-oriented topic into a high-priority topic, with academic attention reaching its top in recent years.

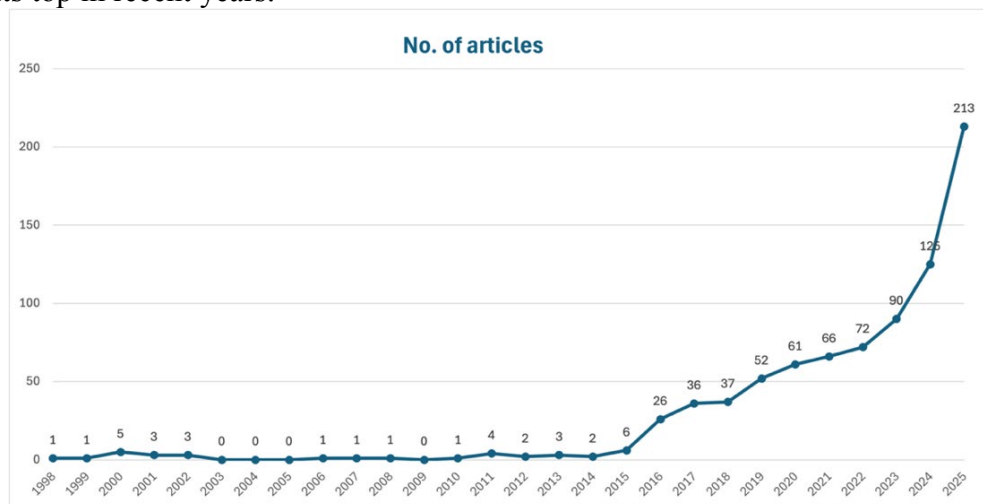


Figure 1. Number of articles published in the selected period

Source: Authors’ owns research results/contribution.

Considering the second research question *RQ2 Which journals and authors are the most influential in the context of AI, fraud and auditing?*, a publication analysis was conducted.

Figure 2 shows the overall distribution of publications retrieved from ScienceDirect across journals. Since this database mainly hosts Elsevier journals, the results primarily reflect research published by Elsevier within the field. It is worth mentioning that even if most of these journals are also indexed in Scopus, the results do not represent the full population of Scopus-indexed journals, as non-Elsevier titles are not included.

The distribution of published articles across journals exposes a particularly irregular pattern. *Technological Forecasting and Social Change* stands out as the principal journal with 51 articles (6.15%) and is followed by the *International Journal of Accounting Information Systems* with 39 articles (4.7%). This suggests that AI, auditing and fraud-related research tend to concentrate in journals that are technology-driven. The second group of journals, ranked based on the number of articles published, is the *International Review of Financial Analysis* (29) with 3.5 % of the total sample population, followed by the *Government Information Quarterly* (25) and *Managerial Auditing Journal* (25), both with 3%. These outlets emphasize the interdisciplinary nature of the field, linking finance, governance and auditing research topics.

Other journals such as *Journal of Business Research* (23), *Technology in Society* (23), *Decision Support Systems* (21) and the *International Journal of Information Management* (21) contribute smaller, but still relevant to the domain. They play an important role in shaping discussions around AI applications in business and information systems. The rest of the journals in the database do not show a significant publication number on this topic, with *Journal of Financial Crime* (13) and *Journal of Accounting Education* (11) being at the lower end of the distribution.

The evidence of publishing distribution reveals important insights. As expected, most of the research revolves around auditing and technology-driven journals. The fact that financial crime publications present little to no interest in the topic suggests that fraud is not typically studied as a main topic, but rather within a broader context. This strengthens the idea that technology and human judgment should balance and complement each other to prevent and detect irregularities.

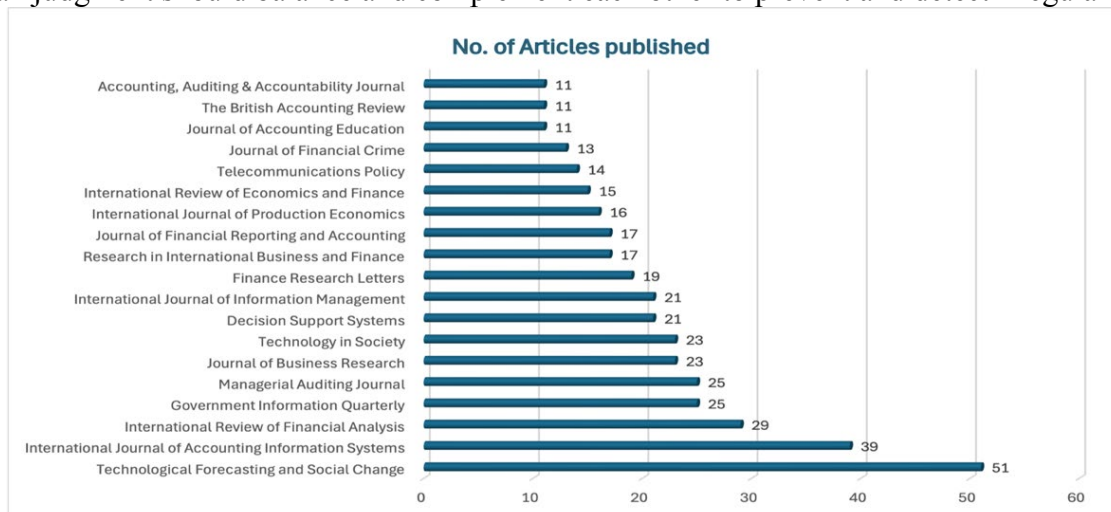


Figure 2. Journals in which articles have been published

Source: Authors' own research results/contribution.

The next section focuses on answering the last research question *RQ3: What are the main themes explored in the literature and how have they evolved over time?*. Starting with the keyword frequency analysis presented in Table 2, the results provide further insight into the main themes included in our dataset. Naturally, ‘artificial intelligence’ appears as the most frequent keyword, followed by terms such as ‘blockchain’ and ‘machine learning’. This finding reflects the strong technological focus of the existing literature.

In contrast, it is important to note the low occurrence of the keyword ‘fraud’, despite it being one of the central topics of this study. This observation is consistent with earlier results, suggesting that financial crime journals do not place significant emphasis on this topic. Instead, fraud appears to be examined mainly indirectly through related concepts such as governance, analytics and risk management rather than treating fraud as a standalone research area.

As a result, a potential gap in the literature has been identified, where fraud-focused studies remain less developed compared to the stronger body of research on AI applications in auditing.

Word	Occurrence
Artificial Intelligence	123
Blockchain	108
Machine Learning	55
Corporate Governance	38
Auditing	23
Digital transformation	22
Sustainability	22
Big data	21
Accounting	18
Literature review	15
Supply chain	13
Corruption	10
Fraud	8

Table 2. Keyword frequency

Source: Authors’ own research results/contribution.

Co-authorship analysis involves exploring the collaborative relationships between authors, based on jointly published scientific papers. In other words, co-authorship analysis is commonly used to identify connections between researchers. This mapping method helps reveal how researchers cooperate and contribute to the development of the academic field.

As shown in Figure 3, the co-authorship network shows a fragmented yet structured collaboration pattern, where authors are grouped into several distinct clusters, each of which represents a research group. The size of each node indicates both the productivity of an author and the extent of their collaborations, while the links between nodes represent co-authored publications. Stronger or more frequent collaborations are represented by thicker links.

From a temporal perspective, lighter or yellow-colored nodes represent more recent contributors, who tend to have fewer links. In contrast, darker or blue nodes represent earlier activity in the field, suggesting that earlier research was characterized by more established collaboration patterns, whereas newer authors are still developing their networks.

Gupta's cluster has the most connections, followed by Dwivedi's cluster. Both authors published during the early period of growing interest in the field, which may explain why they developed stronger and broader collaboration networks over time. The results indicate that authors tend to collaborate more closely with one another than with those outside their group. This suggests that research in this field is still organized around relatively independent teams rather than a closely connected collaboration network. In addition, the existence of many small and medium-sized clusters further strengthens this observation.

Thus, the progression shown in the overlay illustrates how collaboration patterns have evolved and highlights the increasing involvement of new researchers in recent years. At the same time, this pattern may create an opportunity for future studies to encourage greater collaboration between researchers across different disciplines and geographical regions.

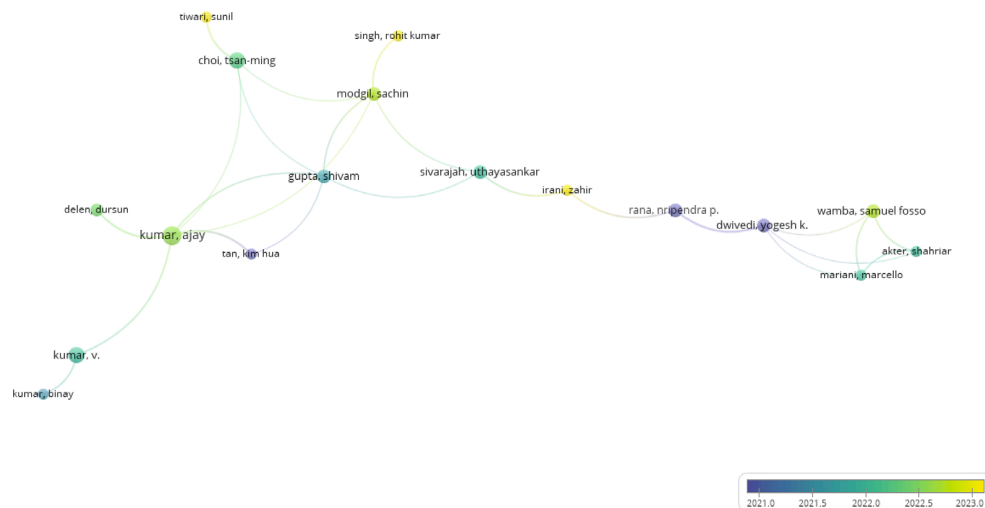


Figure 3. Co-authorship within the articles on AI, audit and fraud detection

Source: VOSviewer.

The co-occurrence analysis highlights the relationships between keywords by showing how frequently they appear together in the existing literature. This approach helps identify the main research trends and discloses areas that have attracted academic interest over the years. The findings indicate a growing interest in topics such as machine learning, algorithmic transparency and data governance. In addition, they emphasize the increasing importance of monitoring, validating and subsequently managing data analysis processes in auditing.

To better understand the most influential topics of artificial intelligence in auditing and fraud detection, we conducted a keyword co-occurrence analysis using publications retrieved from ScienceDirect. The data was processed with VOSviewer software, which, by default, applies a minimum occurrence threshold of 10 keywords. This means that only keywords appearing at least 10 times were included in the analysis.

The output generated consisted of 97 keywords that represent the main concepts discussed in the literature. Based on their relationships and how frequently they appeared together, they were organized into eight distinct clusters, each representing a different thematic research area. In total, 598 connections were identified between the keywords, showing that many topics are frequently

discussed together within the same studies. The total link strength of 948 further suggests that these themes are strongly connected across the literature.

Overall, the results indicate that research in this field is both diverse and closely interconnected, with different topics complementing and influencing one another rather than developing independently.

By organizing the keywords this way, the study offers a structured perspective for interpreting the literature, providing at the same time a more contextualized understanding of the field. In the following sections, we discuss each cluster individually, detailing the keywords that compose it and linking them to relevant studies in the interest field.

The first cluster focuses on core AI applications in auditing and includes keywords such as ‘artificial intelligence’, ‘auditing’ and ‘accounting’. This association reflects the actual context where AI tools are becoming an increasingly important part of the auditing profession and day-to-day processes.

The second cluster includes keywords like ‘machine learning’ and ‘big data’, which is an indicator that the auditors are no longer working only as reviewers of financial information but are becoming users of advanced systems that support faster decision-making.

The first two clusters are in line with the findings from existing literature that suggest that AI helps auditors work more efficiently, due to the ability to process large amounts of data, while supporting activities such as fraud detection and risk assessment. (Kokina et al., 2016; Fedyk et al., 2022; Han et al., 2023; Vasarhelyi et al., 2015).

The third cluster is centered on ‘fraud’, ‘corruption’ and ‘financial crime’, while the fourth explores ‘blockchain’ and ‘transparency’-related applications. Together, these clusters suggest that emerging technologies are becoming increasingly important in strengthening accountability, improving transparency and supporting the detection, as well as prevention of financial misconduct. (Qatawneh, 2024; Chen et al., 2025; Sun et al., 2025; Moffitt et al., 2018; Della Valle & Evangelista, 2025).

The fifth cluster addresses ‘corporate governance’ and ‘accountability’, linking auditing practices to organizational oversight, while the sixth and seventh clusters, which showed significant overlap in the initial analysis, both relate to ‘digital transformation’ and technology adoption challenges. These have been conceptually consolidated, as they address how ready an organization is for innovation and implementation barriers. The presence of keywords such as ‘sustainability’ further reflects the larger strategic and social implications of technological change. (Kroon et al., 2021; Han et al., 2023; Raisch & Krakowski, 2021; Al-Qudah et al., 2025)

The final cluster focuses on ethical considerations, including ‘trust’ and ‘transparency’. This cluster strengthens the academic findings that AI technologies should be used responsibly. Maintaining ethical standards and public confidence remains essential for the successful integration of AI in auditing and financial practices. (Munoko et al., 2020; Brown-Liburd et al., 2015; Al-Qudah et al., 2025; Raisch & Krakowski, 2021).

Source: VOSviewer.

This study provides the results of a bibliometric analysis of research on artificial intelligence (AI) in auditing and fraud detection. Using the quantitative method and the VosViewer software, the analysis covers 829 publications retrieved from the ScienceDirect database, published between 1998 and 2025.

Despite all the advantages that it brings, human oversight remains essential to mitigate biased outputs, transparency issues and excessive reliance on automated systems that could reduce professional judgement. Also, researchers emphasize the need for strong governance structures, standardized workflows and clearer guidance for AI usage and implementation. Moreover, the literature suggests that the field remains somewhat fragmented and with limited evidence regarding AI's impact on audit quality and auditors' responsibility.

In addition, the results suggest that most of the collaborations appear during the early stages of the increasing interest in AI-related publications. This may indicate that collaboration activity intensified when the field began to expand. It also shows that researchers are increasingly recognizing the value of working across different disciplines. Combining expertise can lead to better analysis, wider perspectives and ultimately to robust research outcomes.

Overall, the cluster analysis demonstrates that research on AI in auditing is both interdisciplinary and evolving, merging technological innovation with governance, ethical, and organizational perspectives. It also points to a broader move towards continuous auditing, where insights can be generated in real time rather than only after the completion of audit processes.

At the same time, the overlap between certain clusters suggests that clearer conceptual boundaries are still emerging within the field.

To sum up, the study highlights the transformative impact of AI on auditing practices. AI technologies contribute to increased efficiency, automation of repetitive tasks and enhanced analytical capabilities. However, their effective use depends on auditors' ability to critically interpret outputs and maintain professional judgment, ensuring that AI complements rather than replaces human decision-making.

This study has several limitations that should be considered when interpreting the results. The analysis is based solely on the ScienceDirect database, which primarily includes Elsevier publications and does not fully represent the broader body of literature. In addition, the study does not incorporate citation analysis or co-citation networks, which limits the ability to assess the intellectual structure and influence of individual contributions. These constraints require a cautious interpretation of the findings.

Regarding future studies, several directions emerge from this analysis. For example, studies could focus on the standardization of AI applications in auditing, the development of best practices for human–AI collaboration or the enhancement of auditors' competencies in using advanced technologies. In addition, more empirical and longitudinal research is needed to better understand how AI influences audit quality, fraud detection and risk management across different organizational and regulatory contexts. Future studies could also extend this work by incorporating multiple databases, such as Scopus or Web of Science and by applying more bibliometric techniques, including citation and co-citation analysis. Such approaches would provide a more comprehensive understanding of the field and help identify its most influential studies and emerging research directions.

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