

*Review*

## **Technological convergence in financial auditing: A systematic literature review**

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**Abstract:** Auditing plays a crucial role in ensuring the quality of financial reports. To achieve this, technological tools such as artificial intelligence (AI), blockchain, deep learning, and machine learning are essential in facilitating auditors' work. Thus, we aimed to conduct a systematic literature review (SLR) to consolidate key findings and identify future research opportunities regarding the contributions of AI, blockchain, deep learning, and machine learning to financial auditing. We collected articles from the Web of Science (WoS) database without a predefined time frame. Four search terms were used: i) "Artificial intelligence," "financial," and "audit"; ii) "blockchain," "financial," and "audit"; iii) "machine learning," "financial," and "audit"; and iv) "deep learning," "financial," and "audit." The search resulted in 172 articles. After removing duplicates, inaccessible papers, and those unrelated to the study's objective, we obtained sixty-two relevant studies. The findings indicated that technological tools enable the analysis of large volumes of data, contributing to improved financial reporting quality. As a result, reports become more reliable, enabling users to make more accurate decisions. These technologies also help mitigate the risk of fraud. However, challenges remain, as some professionals perceive potential risks, such as errors in parameter settings. Additionally, the high costs associated with these tools can hinder adoption, particularly for smaller firms. Our findings contribute to the auditing field by highlighting the advantages of integrating these technologies into auditors' daily work and their role in enhancing stakeholder trust. For researchers, this study provides a consolidated theoretical foundation on AI's contributions to auditing, facilitating the identification of trends, challenges, and future opportunities. Even with recent developments, significant gaps remain in the literature regarding the interaction of emerging technologies, such as blockchain, deep learning, machine learning, and artificial intelligence, with auditor independence. These gaps are especially noticeable when it comes to how these technologies affect corporate governance structures,

audit transparency, and tone management in sustainability reporting. Additionally, little is known about the obstacles that small and medium-sized businesses (SMEs) encounter when implementing these advances, particularly those related to technical expertise and infrastructure. Additionally, few empirical studies compare technology-driven audits with those conducted by human auditors, particularly in terms of stakeholder trust, operational efficiency, and the application of professional judgment. Finally, the ethical, legal, and bias-mitigation concerns surrounding the use of technology in auditing remain inadequately addressed by existing theoretical frameworks.

**Keywords:** auditing; artificial intelligence; blockchain; deep learning; machine learning; audit quality

**JEL Codes:** M42, O33

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**Abbreviations:** AI: Artificial intelligence; CEO: Chief executive officer; CFO: Chief financial officer; CRA: Control risk assessment; CSCF: Cost-Sensitive cascade forest; GCC: Gulf cooperation council; IT: Information technology; IFR: Integrated financial reporting; IFRS: International financial reporting standards; KAM: Key audit matters; NLP: Natural language processing; PRISMA: Preferred reporting items for systematic reviews and Meta-Analyses; ROA: Return on assets; SLR: Systematic literature review; UAE: United arab emirates; USA: United states of America; WoS: Web of Science

## 1. Introduction

The auditor plays a crucial role in assessing procedures and regulations to ensure the quality of accounting information. By doing so, the auditor verifies that financial reports are prepared in accordance with thorough verification and validation processes, thereby supporting stakeholders' informed decision-making (Davis et al., 1997; Yang et al., 2024). According to Todorovic et al. (2023), external auditing aims to assess whether financial statements contain material misstatements and subsequently issue an appropriate report for the public, providing a basis for decision-making. Qatawneh (2024) states that, with the right resources, auditing can highlight areas of growth and risk, fostering continuous operational and governance improvements within organizations. Consequently, it ensures that financial and operational data are well-founded, relevant, comprehensive, reliable, and processed in accordance with current accounting standards.

To assist auditors in fulfilling this role, proficiency in IT, readability metrics, and the adoption of emerging technologies such as AI can enhance the effectiveness of audits. These tools enable the analysis of large datasets, improving productivity, efficiency, and accuracy in results (Almaqtari, 2024; Chang & Stone, 2019; Péter & Kocsis, 2024). According to Bortolon et al. (2013), technological advancements have expanded the role and effectiveness of auditing and AI, adding value to organizations by ensuring data accuracy and security. Péter and Kocsis (2024) further emphasized that these technologies facilitate the identification of patterns and anomalies that may go unnoticed in traditional audits, potentially resulting in financial losses.

On the other hand, scalability, information security, and privacy concerns are among the primary challenges, particularly when handling substantial amounts of private financial data without sacrificing openness or legal compliance (Anis, 2023; Péter & Kocsis, 2024). Furthermore, it is challenging to effectively incorporate new technologies into conventional auditing procedures due to their

incompatibility with older systems and the lack of defined regulatory requirements (Alhasana & Alrowwad, 2022). The mismatch between professional training and technical growth is another significant concern (Meredith et al., 2020), as many practitioners lack the necessary skills to interpret, implement, and manage AI- and blockchain-based solutions. This issue is particularly prevalent in small and medium-sized audit firms (Anis, 2023).

The relationship between auditing and AI has been explored from various perspectives: i) Theoretical studies examining AI's contributions to auditing (Hu et al., 2020; Khan et al., 2021; Meredith et al., 2020); ii) studies involving auditing professionals (Yang et al., 2024) and students (Heister et al., 2021); iii) research on how AI helps prevent fraud, mitigate risks (Kerwin & Bastian, 2021; Sushkov et al., 2023), and detect anomalies in financial data (Bakumenko & Elragal, 2022); and predict corporate bankruptcies (Muñoz-Izquierdo et al., 2022).

Building upon these contributions, several literature reviews have sought to organize and synthesize the existing knowledge on the role of emerging technologies in auditing. Meredith et al. (2020) conducted a Systematic Literature Review (SLR) to identify and analyze the factors influencing the adoption and effectiveness of decision-support technologies in auditing. Yang et al. (2024) developed a scoping literature review to understand the interaction dynamics between social actors, AI, and traditional IT technologies in audit processes. Pimentel and Boulianne (2020) reviewed the literature on blockchain in accounting, highlighting current trends and recommending future research opportunities. Alhasana and Alrowwad (2022) conducted a literature review on the peculiarities of national accounting standards in the digitalization era. Sargent (2022) conducted a literature review from the perspective of external financial reporting professionals and their auditors, examining blockchain technology.

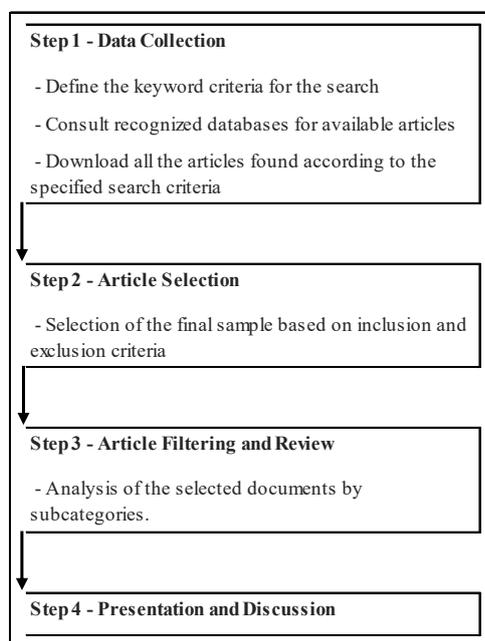
Despite studies linking AI and financial audits, it is evident that most literature reviews do not focus on the contributions of AI, blockchain, deep learning, and machine learning to the audit process. We aim to bridge this gap by highlighting how these technologies can enhance financial auditing. Thus, the guiding research question of our study is: What are the contributions of AI, blockchain, deep learning, and machine learning to the financial auditing process, and what are the possibilities for future research? To answer this question, we aim to conduct a systematic literature review (SLR), consolidating the key findings and identifying future research opportunities regarding the contributions of AI, blockchain, deep learning, and machine learning in financial auditing.

Our SLR can contribute to auditors and researchers. For auditors, the findings can demonstrate the advantages of using these technological resources in their daily activities and their contribution to increasing stakeholder confidence. As a result, financial audits may become more efficient, with reduced risks, optimized time management, and higher-quality information. For researchers, this study provides a consolidated theoretical foundation on the contributions of AI to auditing, enabling the identification of trends, challenges, and opportunities that have not been widely explored in the literature.

This study is divided into four sections: The first section is the introduction. In the second section, we present the materials and methods used to develop this SLR. In the third section, we present the results and discussion of the study, divided into a bibliometric review, SLR, and gaps for future studies. In the last section, we concluded the study.

## 2. Materials and methods

Figure 1 illustrates a summary of the steps taken to construct this study to conform to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach.



**Figure 1.** Methodological Steps for the Systematic Review of the Article (source: Developed by the authors (2025)).

The PRISMA method reduces the risk of bias, provides the reader with clear, robust, and structured results, ensures transparency, and delivers reliable outcomes for decision-making, as it follows precise and reproducible procedures (Khaw et al., 2024).

### 2.1. Data collection

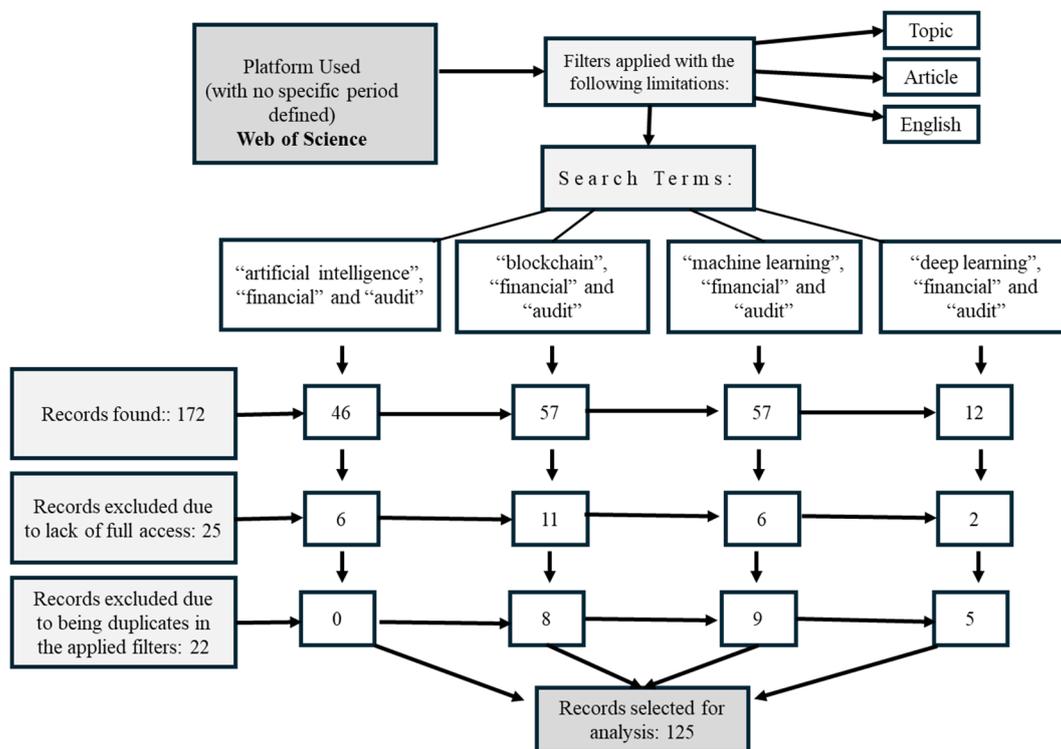
The first step involved collecting articles, which was conducted in January 2025 on the Web of Science (WOS) platform. The choice of this database is justified by its status as one of the largest and most widely used bibliographic databases, providing access to over 36 million articles (Aria & Cuccurullo, 2017).

The collection was limited to articles published exclusively in English and containing the selected search strings, with no specific period limitation to gather all available materials related to the research objective. The search strings were structured using the “AND” connector, with searches conducted in the “topics” field, which included titles, abstracts, or keywords. Four search commands were used, as follows: i) “artificial intelligence”, “financial”, and “audit”; ii) “blockchain”, “financial”, and “audit”; iii) “machine learning”, “financial”, and “audit”; and iv) “deep learning”, “financial”, and “audit”.

The selection of keywords related to artificial intelligence (AI), blockchain, deep learning, and machine learning was guided both by consolidated theoretical foundations in the literature and by the growing relevance of these technologies in the contemporary context of financial auditing. Studies

have shown that these four areas represent the principal axes of innovation capable of redefining the scope, methods, and very nature of audit practice (Appelbaum et al., 2017; Yoon et al., 2015). In this regard, Mohammed Ismail and Abdul Hamid (2024), in a comprehensive systematic review, highlighted that these technologies constitute central pillars of the digital transformation process in auditing, fostering significant advances in automation, large-scale data analysis, and improvements in the quality of audit evidence. Therefore, the choice of these keywords not only reflected alignment with emerging technological trends but was also grounded in a consistent methodological foundation, aligned with the major academic discussions in the field.

The initial search resulted in 172 records. A total of twenty-four articles were excluded due to a lack of access to full-text files, and twenty-two were excluded for duplicates across themes, as shown in Figure 2.



**Figure 2.** Data collection (source: Developed by the authors (2025)).

## 2.2. Selection of articles

The second stage of the PRISMA analysis involved selecting the articles. To achieve this, each author independently reads each article's abstract, objective, and contributions to avoid bias in the final sample selection. This independent analysis considered the experience and background of each reviewer on the subject, enabling them to identify which studies aligned with the research objective. We included only articles from complete years; therefore, four studies published in 2025 were excluded.

Subsequently, we met to align which articles would proceed to the next stage. As a result, some relevant articles were disregarded because they did not directly fit within the scope of AI contributions to the financial auditing process. These studies focused on *specific areas*, such as video analysis for automated compliance, *going concern* prediction, the impacts of COVID-19, the applications of AI in

industries like insurance, higher education, and corporate governance, or topics like *CEO facial masculinity* and tax evasion. Finally, records proposing early warning models using fuzzy techniques and random forest algorithms were excluded, leaving sixty-two records for analysis. We aimed to provide a broader perspective on the contributions of AI, blockchain, deep learning, and machine learning in financial auditing. Due to their specific focus, these excluded studies did not offer the necessary perspective to fulfill this objective.

### 2.3. Filtering and reviewing the articles

In the third stage, based on the final set of sixty-two articles, we developed categories that captured the core ideas of the studies, focusing on succinct and plausible keywords that encompassed topics related to auditing, AI, fraud, blockchain technology, deep learning, and machine learning. These categories were established to identify key discussion points and contributions to our research findings. The constructs were as follows: i) Audit quality (31 articles); ii) risks and/or fraud (14 articles); iii) theoretical studies (10 articles); and iv) comparison between human and machine-performed activities (7 articles).

For classification under the audit quality construct, the articles had to demonstrate how AI, blockchain, deep learning, and machine learning enhanced audit quality, ensuring more reliable and accurate information. The risks and/or fraud constructed focus primarily on the potential of AI to mitigate risks and fraud in auditing processes. The third construct, theoretical studies, included literature reviews such as bibliometric, bibliographic, systematic, integrative, or development literature reviews. Finally, the comparison construct comprised studies that analyzed differences between tasks performed by humans and AI to determine which approach was more effective.

### 2.4. Presentation and discussion

Stage 4 involved presenting and discussing the results developed in the sub-stages. The first involved the bibliometric presentation and discussion of the studies, highlighting the principal authors, leading journals, most cited studies, and the countries most engaged in AI, blockchain, deep learning, machine learning, and auditing research. The second sub-stage focused on presenting and discussing the systematic review, aiming to identify the major contributions of these technologies to the auditing process, which were categorized into the six constructs defined by the authors. In the third sub-stage, we proposed suggestions for future research that, to our knowledge, have not been explored and could significantly contribute to this field of expertise.

## 3. Results and discussions

In this section, we present the bibliometric results, the systematic review, and suggestions for future studies.

### 3.1. Bibliometric analysis

The bibliometric analysis was conducted using the Bibliometrix tool package. The first article published on this topic is from 1997, titled “*Supporting a complex audit judgment task: An expert*

*network approach*,” which aimed to demonstrate how AI techniques can assist in audit judgment, especially in the preliminary evaluation of control risk assessment (CRA). The year with the most publications was 2024, with seventeen studies, followed by 2022 (16) and 2023 (9), representing the last three years analyzed.

Our results align with those of Ruiz-Real et al. (2020), who note that the use of AI, blockchain, deep learning, and machine learning has accelerated. Adopting these technologies can increase revenue and reduce costs in most companies. Jagtap and Sumant (2020) mentioned that by 2026, the growth of the global AI market for business use will be 35.4% annually. They also stated that between 2018 and 2026, the value is expected to rise from \$4.68 billion to \$53.06 billion. Van Noorden and Perkel (2023), after surveying over 1,600 researchers, found that more than 80% believe the use of these technological resources will become essential or very essential for their work. Brynjolfsson et al. (2023) found that AI has significantly increased problem-solving among workers.

Table 1 shows the journals with the highest number of publications. It is noticeable that the sixty-two articles were published in fifty-three different journals.

**Table 1.** Most productive journals.

Journal	Absolute frequency
Financial and Credit Activity-Problems of Theory and Practice	3
Sustainability	3
Intelligent Systems in Accounting, Finance & Management	2
International Journal of Accounting Information Systems	2
Journal of Information Systems	2
Managerial Auditing Journal	2
Review of Accounting Studies	2
Only one publication	46

Source: Own creation

The journals’ *Financial and Credit Activity-Problems of Theory and Practice* and *Sustainability* are the most productive, with three articles each. Following them are five journals with two articles each. The remaining journals published only one study related to the topic, totaling forty-six journals. According to Bradford (1934), there are three zones of productivity, each responsible for approximately 33% of the scientific output on the topic. The first zone contains a few highly productive journals (core journals); the second zone has a more significant number of journals with intermediate productivity; and the third zone includes most journals, each with a few relevant articles (Bradford, 1934). Thus, the results suggest that the articles published in the seven journals with the highest number of publications represent the core zone of scientific production, accounting for 25.8% of the total publications. However, zones 2 and 3 are not clearly visible, as each journal has only one publication in these zones. This low number of publications may be because the topic is relatively new, as 85.5% of the scientific output occurred in the last five years (2020–2024) (Table 2).

Table 2 presents the number of publications by author, totaling 168 works, and the number of publications per year, which totals sixty-two papers.

**Table 2.** Most productive authors and publications by year.

Authors	Absolute frequency	Year	Absolute frequency
BOULIANNE E	2	1997	1
CHEN Y	2	1999	1
DYBALL MC	2	2003	1
GRASSA R	2	2017	1
LI Y	2	2018	2
MARWALA T	2	2019	3
MBUVHA R	2	2020	4
MONGWE WT	2	2021	7
PIMENTEL E	2	2022	16
SEETHAMRAJU R	2	2023	9
WU Z	2	2024	17
ZHANG Y	2		
Only one publication	156		

Source: Own creation

It is observed that twelve authors are responsible for publishing two studies each, representing 7% of the total number of authors. These results do not align with Lotka's Law, which states that the most prolific authors are responsible for approximately 25% of the scientific production in the field. A possible explanation for why a small number of authors are responsible for publishing a significant number of studies is the novelty of the subject, which gained relevance in the last 5 years, during which over 85% of the total production occurred.

Table 3 shows the ten articles with the highest number of citations, considering total and annual citations. Notably, nineteen articles received no citations, twelve of which were published in 2024.

**Table 3.** Most cited articles – Total and annual.

Papers	Total citations	Citations by year
Mining corporate annual reports for intelligent detection of financial statement fraud – A comparative study of machine learning methods	157	17.44
Rough Sets Bankruptcy Prediction Models versus Auditor Signalling Rates	67	2.91
Seeing is believing? Executives' facial trustworthiness, auditor tenure, and audit fees	65	10.83
Establishing the representational faithfulness of financial accounting information using multiparty security, network analysis, and a blockchain	55	7.86
Blockchain in accounting research and practice: Current trends and future opportunities	50	8.33
Man Versus Machine: Complex Estimates and Auditor Reliance on Artificial Intelligence	49	12.25
Corporate distress prediction in China: a machine learning approach	42	5.25
Fintech in financial reporting and audit for fraud prevention and safeguarding equity investments	40	8.00
Client use of blockchain technology: Exploring its (potential) impact on financial statement audits of Australian accounting firms	21	5.25
Fraudulent Firm Classification: A Case Study of an External Audit	20	2.50

Source: own creation

The most cited study is “*Mining Corporate Annual Reports for Intelligent Detection of Financial Statement Fraud – A Comparative Study of Machine Learning Methods*” by Petr Hajek and Roberto Henriques, with a total of 157 citations. This is also the article with the highest number of citations per

year, averaging 17.44. We aimed to examine whether an enhanced financial fraud detection system could be developed by combining specific features derived from financial information and managerial commentary in corporate annual reports. We observe that using machine learning increases the accuracy of classifying companies as fraudulent or non-fraudulent. This result highlights that this article has been the most cited and is a benchmark when discussing using technological resources in auditing.

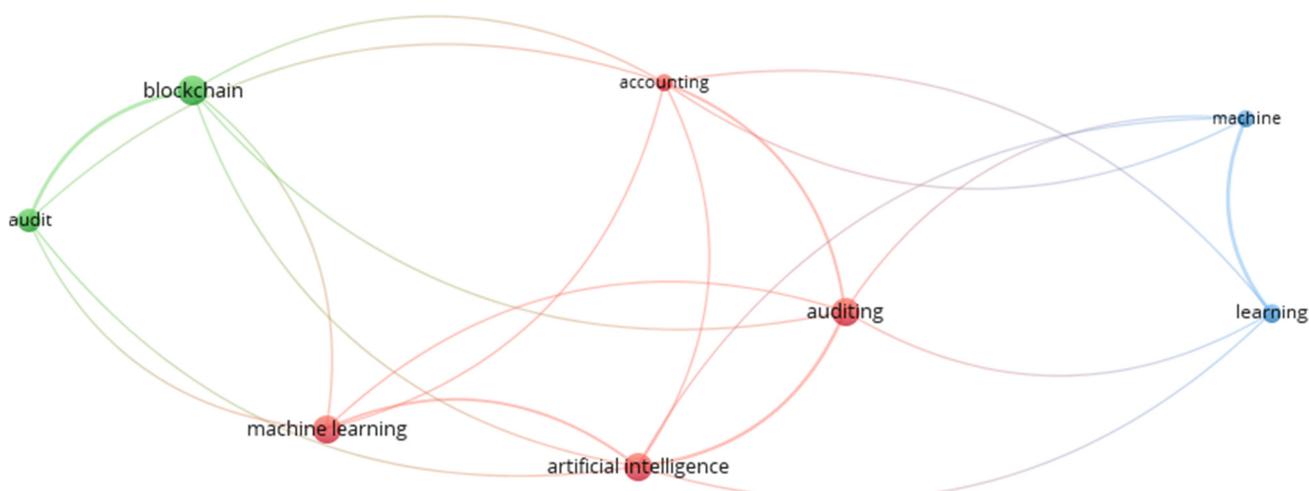
Table 4 presents international collaboration networks. The most frequent collaboration is between China and the United States (3 publications), followed by Australia and Vietnam (2). Other studies with international partnerships have published only one paper each. It is also noteworthy that Chinese researchers have engaged in the highest number of international collaborations (4), followed by the USA and the United Arab Emirates (3), and Australia, Malaysia, Serbia, Lebanon, Thailand, and Pakistan (2 each).

**Table 4.** Collaboration between countries.

Country Collaboration	Absolute Frequency
China and the USA	3
Australia and Vietnam	2
Partnerships with only one publication	13

Source: own creation

Adefila et al. (2023) and Metcalfe and Blanco (2021) highlighted that international scientific collaboration facilitates the advancement of knowledge, the exchange of experiences, and the sharing of diverse resources and perspectives, all of which enrich research. Furthermore, the authors emphasized that international partnerships could enhance the quality and impact of scientific publications.



**Figure 3.** Keyword co-occurrence network (source: Own creation).

Figure 3 presents a co-occurrence network of key terms associated with accounting, auditing, and emerging technologies. This network was generated using the VOSviewer software. The terms *artificial intelligence*, *machine learning*, *blockchain*, and *audit* are strongly interconnected, suggesting an expanding interdisciplinary field. The central connections occupied by *accounting* and *auditing* indicate their structural relevance in the context of applying these technologies. The thickness of the links between the nodes reflects the frequency with which these terms co-occur in the literature,

indicating a research trend focused on incorporating technological innovations into accounting and auditing processes.

Based on these keywords and a careful review of the articles, it is evident that the use of technologies such as blockchain, AI, and advanced machine learning techniques has had a significant impact on financial auditing. These technologies enable the automation of audit processes and the analysis of large volumes of data (big data), contributing to improved audit quality, early fraud detection, and enhanced auditor judgment. However, challenges remain concerning the technological acceptance and the ongoing need for auditors to update their skills to adapt to new methodologies, as well as the regulatory and ethical implications that arise from such innovations.

### 3.2. Systematic literature review

In this section, we present the systematic review results, categorizing the findings according to the four identified constructs.

#### 3.2.1. Audit quality

Table 5 highlights the contributions of studies related to the audit quality construct. In this section, we primarily aim to demonstrate how AI, blockchain, deep learning, and machine learning can facilitate the auditor's work in enhancing auditing quality.

**Table 5.** Contributions of studies on the audit quality construct.

Author (Year)	Objective	Contributions
Hooda et al. (2018)	Explore machine learning algorithms' usefulness in improving audit quality by classifying fraudulent and non-fraudulent companies.	The Bayes Net and J48 models achieved 93% accuracy in classifying companies suspected of fraud, confirming their effectiveness in auditing.
Sánchez-Medina et al. (2019)	Analyze audit quality in small and medium-sized enterprises in Spain and understand how changes affect auditors' decisions regarding going concern reports.	The regulatory change impacted auditors' behavior, increasing the number of going concern reports, where AI was the primary tool for quantifying and understanding financial distress predictions.
Chang and Stone (2019)	Introduce AI-based readability metrics (Coh-Metrix) to examine the effects of firm size on the readability of audit proposals.	The researchers identified that smaller companies produce more readable proposals through AI, while larger firms have a more substantial structural narrative in audit proposals.
McCallig et al. (2019)	Develop an accounting information system that enhances the representational fidelity of financial reporting using multi-party security, network analysis, and blockchain.	The study highlights that integrating blockchain and AI into the financial system enhances audit quality, facilitates fraud detection, and improves financial reporting, thereby increasing trust among investors, stakeholders, and regulators.
Hsieh et al. (2020)	Examine whether auditors' perceptions of client executives' facial trustworthiness are associated with audit fee values.	Audit fees are 5.6% lower in firms where the Chief Financial Officer (CFO) has a trustworthy appearance. Auditor tenure reduces the negative association between CFO facial trustworthiness and audit fees.
Hu et al. (2020)	Identify how AI techniques contribute to audit quality.	The adoption of AI-based audit techniques can enhance the efficiency and effectiveness of audits, resulting in higher-quality financial reports and supporting decision-makers in making more informed and reliable choices.
Heister et al. (2021)	Present a practical exercise to help students understand blockchain concepts and their applications in accounting and auditing.	The study reveals that blockchain is transforming financial record creation and storage, creating new opportunities for data analysis. Students understood the technology and how its returns can support businesses.

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Author (Year)	Objective	Contributions
Mongwe et al. (2021)	Apply Bayesian inference to predict audit outcomes of financial statements for local government entities using financial ratios.	Bayesian logistic regression outperforms traditional models in predicting audit results.
Pimentel et al. (2021)	Systematize the challenges of auditing blockchain-based assets and map these challenges to traditional financial auditing practices.	The study reveals that audit firms hesitate to accept mandates from crypto-asset companies due to the complexities and technical risks of the blockchain sector, for which auditors are not adequately prepared.
Roszkowska (2021)	Explore the causes of financial auditing scandals and highlight how emerging technologies can solve these issues.	Using blockchain, IoT, smart contracts, and AI can reduce fraud, enhance financial reporting quality, and increase the reliability of financial statements.
Abdennadher et al. (2022)	Analyze accountants' and auditors' perceptions of blockchain implementation in the United Arab Emirates (UAE).	The study demonstrates that blockchain has a significant impact on accounting, enhancing transaction recording, evidence storage, and transaction security. It alters auditors' audit process and strategy, complementing traditional auditing with a decentralized, low-cost process and automated evidence collection.
Dai and Zhu (2022)	Establish an intelligent financial audit model that can predict audit opinions on consolidated financial statements.	AI tools improve accuracy in predicting audit opinions, enhancing audit quality and efficiency.
Dyball and Seethamraju (2022)	Investigate the impact of clients' use of blockchain technology on financial audits by Australian accounting firms.	The number of accounting firms with clients using cryptocurrencies or blockchain is small. This creates new risks for audits and may alter how financial audits are planned and conducted.
Elommal and Manita (2022)	Examine how blockchain technology will affect the auditing profession, identifying its implications for audit processes and the business development of audit firms.	Blockchain technology can impact audit firms in six areas: (1) Saving time and improving efficiency; (2) enabling full population audits; (3) focusing on testing controls; (4) establishing continuous audits; (5) playing a more strategic role; and (6) developing new consulting services.
Grassa et al. (2022)	Explore the effect of social distancing due to the COVID-19 pandemic on audit quality in the UAE.	Respondents mentioned that COVID-19 affected materiality assessments, risk evaluations, audit procedures, and evidence collection. They also noted that investments in blockchain could have increased efficiency and communication adaptability between auditors and audited firms.
Muñoz-Izquierdo et al. (2022)	Investigate whether Key Audit Matters (KAMs) disclosed in audit reports contribute to corporate credit rating assessments.	Machine learning increased decision-making accuracy by 74% in determining credit scores based on KAM disclosures.
Ngoc Hung et al. (2023)	Examine the influence and importance of firm characteristics on the quality of financial statements in publicly traded companies in Vietnam.	The most critical factors for financial statement quality are return on assets (ROA), state ownership, firm size, and board size.
Mabelane et al. (2022)	Predict audit opinions in South African municipalities using different feature selection methods and machine learning models.	Artificial neural networks outperform other techniques in predicting audit opinions in South African municipalities, improving audit quality.
Todorovic et al. (2023)	Review and update the set of relevant predictive variables for audit opinion forecasting.	AI enhances audit opinion forecasting through machine learning models like XGBoost, outperforming previous methods.
Almaqtari (2024)	Investigate the role of IT governance in AI integration in accounting and auditing operations.	AI increases efficiency and decision-making capability in accounting and auditing functions, enhances financial reporting quality, improves audit processes, detects anomalies, and boosts predictive analysis.
Arianpoor and Borhani (2024)	Provide a framework for integrating blockchain technology, the audit process, and International Financial Reporting Standards (IFRS).	Fifty-two indicators are identified and classified into eight qualitative characteristics, the most influential being verifiability, timeliness, and predictive value. Experts rate transparency in audit reports highly, suggesting improved auditor judgment quality.

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Author (Year)	Objective	Contributions
Ashraf (2024)	Investigate whether automation improves financial information quality, focusing on the internal control environment.	Automation improves the quality of financial reporting, although it can reduce the demand for human auditors. Automation can initially increase audit fees and committee meetings, but over time, it can minimize oversight, potentially leading to internal control failures.
Cebi et al. (2024)	Develop a decision support system for client acceptance in independent audits.	AI increases objectivity, consistency, efficiency, and fraud prevention and facilitates decision-making.
Dyball and Seethamraju (2024)	Investigate how clients' adoption of blockchain technology impacts the business models of Australian accounting firms.	Companies are gradually adapting their business models, increasing the utilization of blockchain technology and offering value propositions that enhance efficiency and improve the quality of auditoriums.
Estep et al. (2024)	Examine how financial executives perceive and respond to the use of AI in financial reporting and auditing.	Executives recognize the cost of AI but believe its benefits outweigh the expenses, as it improves decision-making, audit processes, and the quality of financial reporting.
Huang et al. (2024)	Investigate the influence of Key Audit Matters (KAM) textual content on firms' financial restatement behaviors.	Companies with worse readability of KAMs, with a negative tone, and a higher level of detail, are more likely to engage in financial revaluation behavior.
Khan et al. (2024)	Investigate how the adoption of AI impacts Integrated Financial Reporting (IFR) in companies listed in the Gulf Cooperation Council (GCC) and the role of audit quality in this relationship.	AI adoption directly impacts companies' IFR in the GCC, with audit quality moderating this relationship. Companies with higher AI adoption have more effective internal financial reporting (IFR), especially when paired with qualified auditors and higher audit rates.
Pham et al. (2024)	Investigate the factors that affect the audit opinion on the financial statements of non-financial companies.	The previous year's audit opinion is crucial in predicting audit opinions. AI allows you to predict audit opinions more efficiently, reduces the time and risk of litigation, and assists in evaluating potential clients.
Qader and Cek (2024)	Investigate the influence of blockchain and AI on company audit quality in Türkiye.	Blockchain and AI improve audit quality by facilitating fraud detection and improving financial reporting, strengthening the confidence of investors and regulators.
Salehi and Oghaz (2024)	Examine its impact on payroll systems, risk management, financial systems, and audit processes.	Blockchain has a positive and significant effect on payroll, risk management, and financial systems. However, the results suggest that blockchain does not significantly impact the audit process.
Subedi (2024)	Investigate how principles-based accounting standards affect auditors' risk perception and audit results.	AI reveals that principles-based financial statements are less risky and that auditors charge fewer audit fees to clients whose statements are based on principles.

Source: own creation

The findings broadly indicate that the use of AI, machine learning, deep learning, and/or blockchain can improve audit quality (Almaqtari, 2024; Cebi et al., 2024; Dai & Zhu, 2022; Estep et al., 2024; Hooda et al., 2018; Pham et al., 2024). Higher audit quality directly impacts financial statements by making them more accurate and reliable, thereby increasing stakeholders' credibility (Almaqtari, 2024; McCallig et al., 2019; Qader & Cek, 2024; Roszkowska, 2021). Furthermore, it can enhance transparency, helping the market better value the company (Abdennadher et al., 2022; Almaqtari, 2024; Huang et al., 2024). These technologies can also be relevant in increasing audit process efficiency (Cebi et al., 2024; Chen et al., 2022; Grassa et al., 2022), leading to more consistent and well-founded decision-making (Cebi et al., 2024).

Throughout the studies, 14 major advantages of using technological tools related to AI, blockchain, deep learning, and/or machine learning in the financial auditing process are identified: i) Reduction in audit process time (Arianpoor & Borhani, 2024; Chen et al., 2022; Estep et al., 2024; Pham et al., 2024); ii) increased confidence in information (Almaqtari, 2024; Chen et al., 2022; McCallig et al., 2019; Qader & Cek, 2024; Roszkowska, 2021; Sánchez-Medina et al., 2019); iii)

reduced risk of fraud (Hooda et al., 2018; McCallig et al., 2019; Qader & Cek, 2024; Roszkowska, 2021); iv) improved risk analysis accuracy (Abdennadher et al., 2022; Almaqtari, 2024; Elommal & Manita, 2022; X. Huang et al., 2024; Mongwe et al., 2021); v) automation of repetitive tasks (Abdennadher et al., 2022; Almaqtari, 2024; Pham et al., 2024); vi) reduction in operational costs (Abdennadher et al., 2022; Dyball & Seethamraju, 2022); vii) full-sample auditing (Abdennadher et al., 2022; Elommal & Manita, 2022); viii) ease in decision-making (Abdennadher et al., 2022; Cebi et al., 2024; Estep et al., 2024); ix) enhancement of audit reports (Dai & Zhu, 2022; Hooda et al., 2018; McCallig et al., 2019; Muñoz-Izquierdo et al., 2022); x) increased security (Abdennadher et al., 2022; Dyball & Seethamraju, 2022); xi) evaluation of potential clients (Pham et al., 2024); xii) prediction of audit opinions (Dai & Zhu, 2022; Mabelane et al., 2022); xiii) increased readability of audit reports (Chang & Stone, 2019); and xiv) audit fee pricing (Hsieh et al., 2020; Subedi, 2024).

AI, in addition to financial reports, can also improve the quality of non-financial reports. Khan et al. (2024) found that companies using AI produce higher-quality IFRs. They also found that the interaction between the audit firm's experience in the sector and the audited company's use of AI enhances the quality of IFR compared with companies without sector experience. However, the relationship is positive; it has lower statistical and economic significance.

Therefore, investments in technologies like blockchain can be highly beneficial for the auditing process (Almaqtari, 2024; Grassa et al., 2022), particularly during periods of economic turbulence, such as the COVID-19 pandemic (Grassa et al., 2022). According to the authors, during this period, there was difficulty in measuring materiality, risks, auditing procedures, and collecting evidence.

Thus, using technological tools based on AI, blockchain, deep learning, and machine learning can improve the quality of financial audits. These tools not only optimize processes but also increase the level of security, accuracy, and reliability of the information analyzed. This enhances operational efficiency, resulting in lower costs, faster processing, higher data analysis volumes, and better resource allocation. In this way, auditing can identify risks, mitigate fraud, and generate information that enables more accurate decision-making. Therefore, integrating AI, blockchain, deep learning, and machine learning tools into financial auditing can support auditors' work and provide reliable, valuable information for stakeholders' decision-making.

Despite the numerous benefits of AI, the implementation of this technology has some negative aspects, identified in the studies as seven key issues: i) Delays in adequate implementation (Estep et al., 2024); ii) high implementation costs (Estep et al., 2024); iii) cybersecurity risks (Dyball & Seethamraju, 2022; Grassa et al., 2022); iv) operational complexity (Pimentel et al., 2021); v) high risks (Dyball & Seethamraju, 2022; Pimentel et al., 2021); vi) lack of accounting standards (Dyball & Seethamraju, 2022); and vii) reduction in demand for human auditors (Ashraf, 2024).

Given the increased complexity and technical risks in the blockchain sector, Pimentel et al. (2021) mentioned that audit firms are hesitant to accept assignments from companies with crypto assets. The authors state that professionals often feel unprepared for this type of service. Therefore, it is recommended that educators adopt such practices in the classroom, as seen in the study by Heister et al. (2021), who found a positive perception among students in building knowledge through an activity focused on blockchain.

It can be concluded that AI has the potential to facilitate the auditor's work during their professional practice. However, challenges must be overcome, mainly related to adequate implementation, high costs, cybersecurity risks, and operational complexities. Therefore, for AI, blockchain, deep learning, and machine learning to be efficient and widely adopted in financial

auditing, companies must adopt strategies to mitigate these challenges, aiming to strike a balance between innovation and security.

### 3.2.2. Risks and/or frauds

Table 6 highlights the contributions of studies on the construct of risks and/or frauds. In this section, we primarily aim to demonstrate how the use of artificial intelligence can reduce risks and/or fraud during the auditing process. This can increase the reliability of financial information, as transparency makes decision-making more accurate. It is also emphasized that the lack of effective controls can make accounting reports more susceptible to errors, manipulation, and deviations, potentially leading to reputational damage and a decline in market value. Therefore, mitigating risks and fraud contributes to a safer corporate environment, strengthening governance and compliance with standards and regulations.

**Table 6.** Presentation of study contributions in the construct of risks and/or frauds.

Author (Year)	Objective	Contributions
Davis et al. (1997)	Demonstrate how AI techniques can assist in audit judgment, especially in CRA.	AI contributes to internal control risk assessment by automating audit judgment tasks. This improves fraud and error detection, increasing the effectiveness of audits and the reliability of financial statements.
Hajek and Henriques (2017)	Developing an enhanced system to detect fraud in financial statements by combining financial information and managerial comments extracted from corporate annual reports.	AI enables the analysis of large volumes of financial and textual data, facilitating the identification of patterns and anomalies that may indicate fraud. It also enables the selection of more relevant variables for fraud detection, improving the accuracy of predictive models and reducing costs with automated systems.
Jiang and Jones (2018)	Develop a corporate bankruptcy prediction model based on the Special Treatment system.	AI enables the analysis of large volumes of data and the identification of anomalies that suggest financial difficulties, improving the accuracy of predictions.
Bakumenko and Elragal (2022)	Develop a solution for anomaly detection in financial data using machine learning techniques.	AI increases the possibility of identifying anomalies and fraud that could go unnoticed with traditional methods. It also facilitates the processing of large volumes of data in a short amount of time.
Chen and Wu (2022)	Develop a new financial fraud detection model that can quickly identify fraud in companies listed in China.	The model based on the stacking algorithm shows better performance in detecting financial fraud than other statistical models.
Huang et al. (2022)	Develop a financial fraud detection model that considers the different misclassification costs and explores the impact of missing value treatments on prediction performance.	Using the cost-sensitive cascade forest (CSCF) method reveals that this approach enhances fraud prediction compared to the RUSBoost model, with notable performance improvements observed when assigning zero values, particularly in comparison to the reference model.
Niu et al. (2022)	Develop a risk audit model based on data mining algorithms to enhance the efficiency and accuracy of the auditing process.	Improvements are observed in the identification of audit risks, the analysis of large data volumes, and the more efficient detection of risks compared to traditional models. Additionally, there is a reduction in the time and resources required for risk identification and increased model accuracy and result reliability.
Zhang et al. (2022)	Detect potential fraud in financial companies through text analysis of annual and quarterly reports from Chinese companies.	The developed model recognizes 77% of fraudulent reports, demonstrating its audit efficiency.

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Author (Year)	Objective	Contributions
Zhang (2022)	Study the role of machine learning algorithms in the dynamic auditing of internet finance.	Machine learning facilitates fraud detection by identifying and preventing abnormal behaviors and recognizing risk patterns, thereby reducing financial losses in affected industries.
Sushkov et al. (2023)	Investigate the integration of data mining techniques, specifically the combination of Benford's Law and machine learning algorithms, to create an enhanced framework for fraud detection in financial control processes.	AI enables the automation and scalability of fraud detection efforts, making the process more efficient and comprehensive. It reduces manual audit costs, improves fraud detection accuracy, and increases organizational efficiency.
Zhou et al. (2023)	Develop a financial fraud detection model that integrates audit opinions, using Natural Language Processing (NLP) techniques and machine learning to improve fraud detection accuracy in publicly listed companies in China.	There is an improvement in detecting financial fraud compared to conventional models. The integration of audit opinions enhances the model's accuracy and detection capability.
Qatawneh (2024)	Understand how NLP can improve the effectiveness of AI in detecting and preventing fraudulent activity.	AI improves auditing and fraud detection accuracy and efficiency by automating routine tasks, analyzing large volumes of data, and providing valuable insights into potential risk areas.
Tragouda et al. (2024)	Develop models to identify fraud in financial statements using a multi-label classification approach based on the fraud diamond theory.	The multi-label classification approach not only detects fraud but also considers auditors' comments, providing better results compared to binary methods and avoiding inconsistencies in financial manipulation analyses.
Wang and Zhu (2024)	Build a financial fraud prediction model based on machine learning methods for listed companies.	The model is more effective in predicting financial fraud than traditional logistic regression methods. It also enables the automated analysis of large volumes of data, resulting in less time and resources needed to identify fraud.

Source: Own creation

The results highlight that AI plays an essential role in detecting fraud (Chen & Wu, 2022; Davis et al., 1997; Qatawneh, 2024; Wang & Zhu, 2024). The major benefits found are: i) Analysis of large data volumes (Hajek & Henriques, 2017; Jiang & Jones, 2018; Niu et al., 2022); ii) machine learning capability and adaptation to new frauds (Bakumenko & Elragal, 2022; Zhou et al., 2023); iii) lower costs (Hajek & Henriques, 2017; Huang et al., 2022; Sushkov et al., 2023); iv) increased predictive efficiency (Chen & Wu, 2022; Niu et al., 2022; Qatawneh, 2024); v) identification of variables most associated with fraud (Hajek & Henriques, 2017); vi) risk assessment and monitoring (Qatawneh, 2024); vii) real-time evaluation (Qatawneh, 2024); viii) reduced time to identify fraud risks (Bakumenko & Elragal, 2022; Niu et al., 2022; Wang & Zhu, 2024); ix) reduced risks of weak internal controls (Wang & Zhu, 2024); and x) increased reliability of financial numbers (Davis et al., 1997; Niu et al., 2022; Wang & Zhu, 2024).

Given the results presented, it is evident that AI, blockchain, deep learning, and machine learning play important roles in fraud detection, contributing to auditing and decision-making by stakeholders. Using these technological tools also contributes to cost reduction in auditing, particularly in terms of reducing operational labor. These benefits are mainly generated by the ability of these tools to process large data volumes, learn, and adapt to new frauds, and present lower costs. Therefore, by leveraging AI, blockchain, deep learning, and machine learning, organizations can offer greater protection against financial losses, and stakeholders can make informed decisions with confidence.

On the other hand, the use of AI, blockchain, deep learning, and/or machine learning faces significant challenges. The complexity of algorithms and the need for robust databases can hinder the adoption of such technologies, especially in smaller companies with limited resources (Chen & Wu, 2022; Niu et al., 2022; Wang & Zhu, 2024). Another aspect concerns ethical issues, particularly regarding data privacy and the risk of algorithmic bias, which may lead to inaccurate or discriminatory conclusions (Coeckelbergh, 2019). It should also be emphasized that these tools do not replace human expertise, and it is necessary to balance automation with specialized supervision to ensure more accurate and contextualized analyses (Michel-Villarreal et al., 2023).

### 3.2.3. Theoretical studies

Table 7 highlights the contributions of research related to the construct of theoretical studies. In this section, we aimed to identify how researchers have investigated the contributions of AI, blockchain, deep learning, and machine learning to auditing from a theoretical perspective. Bibliometric and/or systematic literature review articles were considered.

**Table 7.** Presentation of studies' contributions in the construct of theoretical studies.

Author (Year)	Objective	Contributions
Meredith et al. (2020)	Conduct a systematic review of the literature on the use of decision support technologies in auditing, identifying, and analyzing the factors that influence their adoption and effectiveness.	Decision support technology can improve the quality of financial audits by increasing accuracy, efficiency, and transparency.
Alles and Gray (2020)	Develop a framework to understand the automation of the auditing process and its impact on stakeholders' trust in audited financial statements.	AI can automate manual tasks, enabling auditors to focus on advanced analysis and professional judgment. It is also observed that AI improves predictive analysis and reduces human errors, increasing the quality, efficiency of audits, and transparency.
Pimentel and Boulianne (2020)	Review the literature on blockchain in accounting, highlighting current trends and recommending opportunities for future research.	The sixty-four articles reviewed showed that blockchain increases data reliability and security, eliminates unnecessary reconciliations, enhances transparency and traceability, automates audit processes, reduces costs and time, and improves audit quality. However, successful adoption requires overcoming technical challenges and acquiring new skills from professionals in the field.
Jiang (2021)	Develop the preprocessing process for collecting, clarifying, and storing big data, and build a framework for the simulation process of significant data auditing under the service model.	AI and big data technology development can improve traditional auditing methods by introducing new approaches that allow more efficient data collection, analysis, and processing. This facilitates the identification of issues and anomalies in non-financial businesses and improves the accuracy and effectiveness of audits.
Alhasana and Alrowwad (2022)	Study the peculiarities of national accounting standards in the digitalization era and propose ways to develop these standards, especially regarding cryptocurrency accounting approaches.	Through a literature review, the authors concluded that there is a significant challenge in the proper recognition and measurement of cryptocurrencies.
Sargent (2022)	Conduct a literature review to examine the characteristics of blockchain technology from the perspective of those responsible for external financial reporting and their auditors.	The analysis of the eighty-one articles reveal that consensus verification, often seen as a substitute for external auditors, does not provide sufficient evidence for financial statement audits. The researchers conclude that while blockchain simplifies some auditing tasks, physical verification and the assessment of estimates and allocations are required.

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Author (Year)	Objective	Contributions
Olendiy et al. (2023)	Identify trends, the current state, and prospects for the development of tax audits.	AI in tax auditing is essential to ensure the accuracy of financial reports and tax compliance in the business services industry.
Prokofieva (2023)	Develop a framework that maps data analysis to the stages of auditing and provide guidance on implementing this framework in the teaching of auditing with AI and machine learning.	Training in AI and data analysis is essential to prepare auditors for the profession's challenges in the digital age.
Shapovalova et al. (2023)	Develop a concept to modernize the national accounting policy to improve the efficiency, quality, and transparency of accounting and auditing processes.	The use of AI enables the automation of routine tasks, contributing to the reduction of costs and time. Additionally, it enables the analysis of large volumes of data in real-time. AI also enhances fraud detection, forecasting, improvement, and transparency of financial reports, enabling more strategic and reliable decision-making.
Yang et al. (2024)	Develop a literature review to understand the interaction dynamics between social actors, AI technologies, and classical IT in auditing processes.	The researchers identify that AI offers opportunities to improve decision-making, automate processes, and enhance the workforce's capabilities in financial auditing. However, it also presents challenges, such as accountability gaps and replicating existing practices.

Source: own creation

Based on different literature review metrics, the results show that the use of AI, blockchain, deep learning, and machine learning improves auditors' performance, mostly regarding effectiveness and data processing for decision-making (Meredith et al., 2020; Yang et al., 2024), financial fraud detection (Meredith et al., 2020), automation of repetitive tasks (Meredith et al., 2020; Sargent, 2022; Yang et al., 2024), cost reduction (Pimentel & Boulianne, 2020), accuracy of accounting reports (Meredith et al., 2020; Olendiy et al., 2023), and increased transparency and reliability (Meredith et al., 2020; Pimentel & Boulianne, 2020). As a result, auditors have more time for higher-value activities (Meredith et al., 2020).

However, Arnold et al. (2023) mentioned that when professionals become overly dependent on technologies for decision-making, their skills can be reduced, resulting in a phenomenon known as deskilling (Arnold et al., 2023). Deskilling can occur when professionals lose previously acquired knowledge due to a lack of use and when new professionals fail to develop skills traditionally acquired through experience (Sutton et al., 2023). This becomes more impactful in developing auditors' expertise, mainly due to the growing reliance on auditing support systems (Arnold et al., 2023; Dowling & Leech, 2014). Therefore, this dependence can hinder knowledge acquisition in the long run, reducing auditors' ability to perform audits independently and effectively.

#### 3.2.4. Human versus machine

Table 8 highlights the contributions of studies to comparing activities performed by humans and machines. Our focus of this topic is to identify whether using machines increases assertiveness and improves the quality and reliability of accounting numbers when compared to activities performed by humans.

**Table 8.** Presentation of the contributions of the studies in the construct of the comparison between activities performed by humans and machines.

Author (Year)	Objective	Contributions
Anandarajan and Anandarajan (1999)	Examine the predictive accuracy of machine learning techniques in forecasting the type of audit report to be issued in situations of uncertainty regarding going concern.	The comparison results among the three models show that using artificial neural networks achieved the highest accuracy (85.8%), followed by Multiple Discriminant Analysis (74.1%), and finally, the Expert Systems model with 69.1%.
McKee (2003)	Compare models based on rough set theory with auditors' disclosure rates for the same set of companies.	The results suggest that rough set models do not offer a significant comparative advantage over current auditing methodologies.
Khan et al. (2021)	Develop an AI-based auditing tool to audit textual evidence and determine its efficiency and effectiveness.	Using the AI tool results in 92% efficiency while achieving 95% effectiveness, indicating confidence in the tool's adoption.
Commerford et al. (2022)	Analyze how auditors react to adjustments proposed in financial reports from an AI system compared to a human expert.	Auditors show lower acceptance of adjustments based on evidence from an AI system than when they use evidence from a human expert.
Chen et al. (2022)	Propose a population-based audit method using machine learning to improve the efficiency of internal control audits.	Using machine learning for population-based auditing is viable and can replace manual work in financial auditing. The method has a high accuracy rate in identifying accounting anomalies, outperforming sample-based audits.
Zeng et al. (2022)	Predict audit opinions using machine learning, aiming to provide technical support for auditors and enhance the quality of financial reports.	The use of machine learning enhances the prediction of audit opinions, contributing to the improvement of the quality of financial reports.
Nguyen et al. (2024)	Explore perceptions related to the suggestion that external auditors will be replaced by auditing technologies using AI tools to make audit judgments when conducting financial statement audits.	AI-based auditing technologies increase the efficiency of accounting and auditing activities. However, AI cannot fully replace auditors; instead, it can facilitate their work.

Source: own creation

The results are mixed when comparing the use of machines and human work. McKee (2003) found that when comparing rough set-based models and human forecasting, the models predicted 61% of bankruptcies, while auditors directly identified continuity issues in only 54% of companies that later declared bankruptcy. Using other opinion modifications, the auditors' signaling rate increased to 66% and the machines' to 68%.

Khan et al. (2021) found that the AI tool helps audit textual evidence, achieving 92% efficiency and 95% effectiveness. Chen et al. (2022) found that using AI reduces incorrect statements in the accounting treatment of business transactions and abnormal business cases where accounting rules are not clearly formulated. Also, according to Chen et al. (2022), implementing AI tools can increase the efficiency and reliability of audit conclusions, corroborating the idea by Nguyen et al. (2024) that AI-based auditing technologies increase the efficiency of accounting and auditing activities as a whole.

Commerford et al. (2022) found that auditors are averse to adjustments suggested in financial statements. This aversion can lead auditors to undervalue evidence produced by AI systems, as these are considered less reliable than human experts. This factor could lead auditors to more easily accept estimates provided by management, especially regarding more objective forecasts. Auditors' aversion to AI can hinder the adoption and effective implementation of AI technologies in the auditing environment.

Anandarajan and Anandarajan (1999) mentioned that expert systems (which heavily rely on human knowledge, as they are designed to replicate decision-making by specialists in a specific

domain) are less efficient in predictive accuracy regarding the type of audit report to be issued. However, because AI excels in repetitive processes and activities (Khaw et al., 2024), it enables professionals to have more time to take on more strategic roles that require greater professional judgment in decision-making. Therefore, AI is essential but does not replace the auditor.

### 3.3. Gap for future research

The gaps for future research are presented by theme, as shown in Table 9.

Notably, all the suggested analyses can be made comparative: i) Developed and emerging countries; ii) before, during, and after the pandemic; iii) audits performed by BIG4 versus non-BIG4 firms; and iv) companies with high and low corporate social responsibility. Therefore, there are many opportunities for future studies, making this a promising field.

**Table 9.** Gaps for future research.

Theme	Gaps
Audit quality	<ul style="list-style-type: none"> <li>i) Identify how the interaction between audit independence and the use of AI, blockchain, deep learning, or machine learning can enhance the quality of audit reports;</li> <li>ii) Identify how the use of AI, blockchain, deep learning, or machine learning in cooperative audits can improve audit quality;</li> <li>iii) Investigate the influence of visual rhetoric in corporate reports on stakeholder perception;</li> <li>iv) Assess the effects of blockchain adoption on the transparency and reliability of accounting information;</li> <li>v) Explore challenges and barriers in the adoption of AI, blockchain, deep learning, or machine learning by SMEs, including knowledge and infrastructure gaps;</li> <li>vi) Analyze the relationship between the use of AI and blockchain and tone management in audited sustainability reports;</li> <li>vii) Study the impact of blockchain implementation on corporate governance and internal control;</li> <li>viii) Investigate the effect of adopting emerging technologies on the recruitment and qualification of auditors;</li> <li>ix) Examine the cost-benefit of automation in the audit sector and its impact on operational efficiency;</li> <li>x) Explore the relationship between corporate governance levels and the adoption of emerging technologies in financial auditing;</li> <li>xi) Investigate the use of AI in the analysis of Chief Executive Officer (CEO) and Chief Financial Officer (CFO) speeches to predict accounting manipulations and financial fraud;</li> <li>xii) Investigate how AI, blockchain, deep learning, or machine learning can enhance the quality and comparability of integrated financial reports across different sectors.</li> </ul>
Fraud and/or Risks	<ul style="list-style-type: none"> <li>i) Investigate the integration of different machine learning algorithms to optimize audit risk identification models and improve model interpretation;</li> <li>ii) Explore the application of machine learning algorithms in fraud scenarios;</li> <li>iii) Utilize AI and machine learning algorithms in real fraud cases to verify their ability to predict previously occurred frauds;</li> <li>iv) Develop fraud detection models that integrate both financial and non-financial data;</li> <li>v) Explore the impact of macroeconomic variables on corporate bankruptcy prediction;</li> <li>vi) Investigate the influence of different ownership structures and corporate governance on bankruptcy prediction using AI, deep learning, or machine learning tools;</li> <li>vii) Explore the inclusion of textual information, such as manager personality traits, shareholder comments, and company-related news, to enhance fraud detection;</li> <li>viii) Analyze the relationship between ESG practices and AI, blockchain, deep learning, or machine learning in mitigating fraud risks.</li> </ul>

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Theoretical Studies	<ul style="list-style-type: none"> <li>i) Identify the leading strategies and methods of AI, blockchain, deep learning, and machine learning employed in auditing to improve the quality of analyses and detection of irregularities;</li> <li>ii) Conduct a bibliometric review to examine the evolution of research on AI, blockchain, deep learning, and machine learning in auditing and fraud detection, identifying trends and gaps in the literature;</li> <li>iii) Conduct a systematic review to identify the impact of AI, blockchain, deep learning, and machine learning on the accuracy and reliability of audited financial reports;</li> <li>iv) Conduct an integrative review to highlight the challenges and opportunities of using AI, blockchain, deep learning, and machine learning in auditing, considering ethical, regulatory, and technical aspects;</li> <li>v) Identify the most significant applications of machine learning, deep learning, and machine learning in auditing and their effectiveness in identifying financial fraud;</li> <li>vi) Conduct a literature review to assess the efficiency of AI, blockchain, deep learning, and machine learning in automated audits versus traditional human-conducted audits;</li> <li>vii) Examine the impact of AI, blockchain, deep learning, and machine learning on mitigating biases and human errors during the financial audit process;</li> <li>viii) Identify the major predictive models based on AI used in auditing for detecting anomalies and accounting fraud;</li> <li>ix) Conduct a literature review to analyze how the adoption of AI, blockchain, deep learning, and machine learning in auditing impacts stakeholders' perception of the reliability of financial reports;</li> <li>x) Conduct meta-analyses to identify the relationship between AI, audit quality, and/or AI and fraud.</li> </ul>
Comparison Between Human and Machine-Developed Activities	<ul style="list-style-type: none"> <li>i) Investigate the limitations of AI, blockchain, deep learning, and machine learning in auditing regarding the subjective interpretation and professional judgment of human auditors;</li> <li>ii) Analyze the ability of AI, blockchain, deep learning, and machine learning to identify fraud patterns compared to the experience and intuition of human auditors;</li> <li>iii) Examine how collaboration between AI, deep learning, and machine learning, and human auditors can optimize fraud detection and the quality of audits;</li> <li>iv) Compare the speed of data processing and analysis between human auditors and machine learning algorithms in the evaluation of financial statements;</li> <li>v) Investigate auditors' acceptance and resistance to the use of AI, blockchain, deep learning, and machine learning as support tools in auditing and fraud detection;</li> <li>vi) Compare stakeholders' trust in audits conducted exclusively by humans and those using AI and machine learning techniques;</li> <li>vii) Identify areas of auditing where AI surpasses human capabilities and areas where human expertise is irreplaceable.</li> </ul>

Source: own creation

#### 4. Conclusions

Our objective was to conduct a systematic literature review (SLR), consolidating the major findings and identifying opportunities for future studies on the contributions of AI, blockchain, deep learning, and machine learning in financial auditing. Our data were collected from WOS without a specific time frame, resulting in an initial sample of 172 articles and a final sample of sixty-two studies. We grouped the articles into four constructs: Audit quality, risks and/or frauds, theoretical studies, and comparison between human-developed and machine-developed activities.

Our findings show that using AI, blockchain, deep learning, and machine learning enables analyzing large volumes of data, increasing predictive capacity, reducing audit process time, reducing fraud risks, lowering operational costs, and enhancing audit reports. On the other hand, implementing these technologies can be time-consuming and expensive, exposing audits to cyberattack risks and potentially reducing the roles of human auditors.

Given this scenario, it is concluded that the benefits derived from using AI, blockchain, deep learning, and machine learning tools can enhance the quality of audit reports, leading to more reliable reports and more accurate decision-making by stakeholders. The study is limited to the analysis of

only one database, which may result in the exclusion of relevant studies. There may also have been some bias in the selection and categorization of the studies despite the use of rigorous inclusion and exclusion criteria.

Based on the gaps identified in the literature, this study opens avenues for several future research agendas. It is recommended, for instance, to deepen the analysis of how the interaction between auditor independence, and the use of emerging technologies, such as AI, blockchain, deep learning, and machine learning, can enhance the quality of audit reports. Moreover, comparative studies between audits conducted exclusively by humans and those supported by intelligent technologies may provide relevant evidence on the efficiency, reliability, and stakeholder acceptance of these tools. Examining the effects of small and medium-sized businesses' adoption of emerging technologies while considering the institutional and technical obstacles these businesses confront is another exciting direction. Investigating the capacity of these technologies to identify patterns of financial fraud is also pertinent, particularly when combined with textual data and ESG indicators. Last, to map gaps, compile current information, and direct future research on the application of disruptive technologies in auditing and fraud detection, systematic reviews and meta-analyses are advised.

### **Author contributions**

Dryelle Laiana De Jesus Silva Dos Santos<sup>1</sup>: Collection, processing, and analysis of articles; introduction; methodology.

Geovane Camilo Dos Santos: Analysis of articles; review of introduction and methodology; results, conclusion, and references.

### **Use of AI tools declaration**

The authors declare they have not used Artificial Intelligence (AI) tools in creating this article.

### **Conflict of interest**

All authors declare no conflicts of interest in this paper.

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