BIBLIOMETRIC ANALYSIS OF ARTIFICIAL INTELLIGENCE TRENDS IN AUDITING AND FRAUD DETECTION

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OPEN ACCESS

How to cite this paper:
Ramos, S., Perez-Lopez, J. A., & Abreu, R. (2024). Bibliometric analysis of artificial intelligence trends in auditing and fraud detection [Special issue]. *Corporate Governance and Organizational Behavior Review, 8*(2), 330–342.
https://doi.org/10.22495/cgobrv8i2sip8

ISSN Online: 2521-1889
ISSN Print: 2521-1870

Received: 25.01.2024
Accepted: 11.06.2024

JEL Classification: M4, M42
DOI: 10.22495/cgobrv8i2sip8

Abstract

This research identifies trends in artificial intelligence (AI) in auditing and fraud detection using a combination of two methods: a bibliometric and a systematic review of AI trends in auditing in fraud detection. This research develops a bibliometric analysis of 1,348 papers on “fraud”, “auditing”, and “artificial intelligence” from 1986 to 2022. The results provide a robust set of information for in-depth research on AI trends in auditing and security detection. They not only demonstrate that there is growing academic interest in the research topic of fraud but also show clear evidence that the words “fraud”, “crime”, and “fraud detection” were the most cited, generating a great impact in the literature and developing concern with the topic. Our analysis suggests that the application of AI allows for greater facilitation of procedures to combat fraud and irregularities in the field of criminal justice and fundamental rights. Most technological changes increase ethical motivations to deter fraud, and these changes will lead to a long-term decrease in the incidence of fraud (Karpoff, 2021). This research contributes to AI valuing in audit procedures to detect and prevent fraud and simultaneously mitigate it. It also contributes to the literature, highlighting trends in AI, auditing and fraud detection, thereby enabling the development of professional judgment on the topic and providing direction for future investigations.

Keywords: Bibliometric Analysis, Artificial Intelligence, Audit, Fraud, Crime

Authors’ individual contribution: Conceptualization — S.R., J.A.P.-L., and R.A.; Methodology — S.R.; Software — S.R.; Validation — J.A.P.-L. and R.A.; Formal Analysis — S.R., J.A.P.-L., and R.A.; Investigation — S.R., J.A.P.-L., and R.A.; Resources — S.R. and R.A.; Data Curation — S.R.; Writing — Original Draft — S.R., J.A.P.-L., and R.A.; Writing — Review & Editing — J.A.P.-L. and R.A.; Visualization — S.R. and R.A.; Supervision — J.A.P.-L. and R.A.; Project Administration — S.R. and R.A.; Funding Acquisition — R.A.

Declaration of conflicting interests: The Authors declare that there is no conflict of interest.

Acknowledgements: The Authors aim to thank David Crowther for the support. The Authors also would like to acknowledge that this research is financed by national funds through the Foundation for Science and Technology (FCT), Public Institute, within the scope of multi-annual funding UIDB/04043/2020 and UIDP/04043/2020.

1. INTRODUCTION

With the evolution of society and technology, there is an increasing need for auditors to review their paradigms and adapt their know-how to the new challenges that arise in digital transformation. Pizzi et al. (2021) argued that this choice of procedure cannot be voluntary due to its disruptive impact on organisations. These changes are equally important in more easily detecting types of fraud in other organisations (Hashimzade et al., 2010). Bermeo-Giraldo et al. (2021) argued that fraud is occurring more and more easily in organisations because it is carried out by employees, directors, owners, shareholders or managers to obtain money, goods or services or to secure personal advantage, evade taxes or to obtain shareholders or credit from companies' access. Mutschmann et al. (2022) commented that fraud detection needs external staff to conduct the audit task that provides protection against such unethical practices and manipulation.

The adaptation and adequacy of artificial intelligence (AI) in auditing practices plays a vital role in detecting fraudulent practices given that fraud-related activities are growing at a dizzying pace and cause substantial economic losses every year (Sánchez et al., 2021). According to Nurkey et al. (2021), the effect of corruption felt by a country's residents is due to its negative impact on the economy.

However, indicators within this model are currently influenced by specific tools, such as electronics, information and communication technology, which reduce the risk of fraud and corruption.

Information, communication and electronic technologies promote the area of AI and increase its scientific development. Laufs and Borrion (2021) mentioned that the use of technology has been an important part of police work and its evolution. Thus, AI is increasingly valuable in the day-to-day life of ordinary citizens as well as in businesses and public administrations. AI is useful in specific contexts in all types of procedures, such as combating fraud and irregularities in the field of criminal justice and regarding the impact of fundamental rights (Castellano, 2021). The ongoing digital transformation is visible in the tax world (Kowal-Pawul & Przekota, 2021).

An examination of previous studies reveals that several mechanisms have already been developed using AI to help detect fraud in different areas, making it increasingly important to create innovative AI tools in combating the diverse crimes, corruption and economic problems caused by fraud. These technological innovations increase the ethical motivations for deterring fraud; consequently, these changes will lead to a long-term decrease in the incidence of fraud.

Bibliometric analysis originated in the field of library economics and information science (Merigó & Yang, 2017) but has become a fundamental methodology for the analysis of research as well as an excellent tool for documenting the nature of literature and literature trends and trajectories (Subramanian et al., 2023). Bibliometrics usually includes two procedures, performance analysis and scientific mapping analysis (Gaviria-Marin et al., 2018, 2019). According to Ellegaard and Wallin (2015), bibliometrics is strictly associated with the wider term "informetric", and bibliometric methods are employed to provide quantitative analysis of papers. Bibliometrics is widely used to summarise the most representative results from a set of bibliographic documents (Martínez-López et al., 2018). Its techniques include impact indicators, citation and co-citation analysis and bibliometric mapping (Danvila-del-Valle et al., 2019). Through these techniques, it is possible to analyse the most influential papers in a research field to understand the intellectual dynamics of that field (Donthu et al., 2021).

There is little literature demonstrating the importance of new AI trends in audit procedures in fraud detection through bibliometric analysis. Scientific research is crucial to promoting innovation and expanding knowledge (Jacob & Meek, 2013), Therefore, this research must be undertaken to fill this gap.

This article makes several contributions. First, it identifies AI trends and their value in audit procedures to detect and prevent fraud and, at the same time, mitigate it. Second, this article sheds light on AI trends and concerns about the use of AI in fraudulent and criminal practices. Third, this article represents the first study to conduct a bibliometric analysis of trends in AI in auditing and fraud detection, which according to Kumar et al. (2023), represents an important effort to help interested academics and professionals gain scientific insight into existing research in the area. Although there are bibliometric analyses on AI, auditing and fraud, they remain limited as they are found in individual analyses and in different contexts. Lastly, the use of a mixed approach in this review involving a bibliometric analysis and a literature review overcomes the shortcomings of previous reviews.

This research identifies trends in AI in auditing and fraud detection through bibliometric analysis and a broad literature review to better understand this line of research and to answer the following questions:

RQ1: What is the volume of papers published in the field of fraud in the areas of artificial intelligence and auditing?

RQ2: What are the most influential journals in these studied areas?

RQ3: Who are the authors with the most publications on this topic and in which countries?

RQ4: What are the most repeated words in papers?

Thus, this research presents the alignment of knowledge between the literature review and bibliometric analysis, which allows the gaps to be filled since there was no specific research on AI trends in auditing fraud detection, thereby contributing to scientific knowledge.

To meet the objectives of this research, the first task was to form a database from published papers on fraud and, subsequently, to identify the areas of auditing and AI discussed in the papers. The methodological procedure for the bibliometric analysis established a population of 1,348 papers published in the Scopus database until January 2022. The literature analysis was carried out in a descriptive way based on the most impactful papers that demonstrated the trends in AI in auditing and fraud detection.

The rest of the article is organized as follows. Section 2 presents a literature review in which AI is analysed in relation to audit procedures and its usefulness in combating fraud. Section 3 describes the methodological approach used in the research. Section 4 consists of a descriptive analysis of the main results and reflections on the main implications of the research. Section 5 outlines the final considerations.

2. LITERATURE REVIEW

2.1. Trends in artificial intelligence in auditing and fraud detection

Combining the AI concept with the audit concept seems like a good way to approach the new fraud detection paradigm. Technological innovation through AI has caused significant changes in many aspects of life, mainly in professions such as accounting and auditing that positively contribute to improving analytical auditing procedures, information sharing and fraud detection, which will consequently have a significant impact on the digital economy, future professions and the way people live and interact in the future (Huson et al., 2024).

Due to the uncertainty of the factors that determine the likelihood of fraud, fraud detection has become a challenging task that requires talent and technology (Tang & Karim, 2019). It is essential to develop different types of technologies to deal with the complexity of fraud detection and increase effectiveness.

Through AI, several mechanisms have already been developed to help detect fraud in various areas. An example is the ConTrib application, which is a mechanism created by de Vos and Pouwelse (2021) that maintains fairness in decentralised applications, such as accounting programmes, that use a simple fraud detection algorithm, tolerate significant packet losses and have relatively fast fraud detection times. The capability to exactly and reliably discover anomalies in time series is crucial in fraud detection and information security. Zhang, Zhang, et al. (2021) explained their research using AI to create a programme called AURORA for the recognition of anomalies in seasonal multivariate time series. AI-based systems are becoming increasingly crucial for decision-making in various environments and offer a wide range of opportunities (Weber et al., 2024). Nicholls et al. (2021) argued that there are several intelligent methods, such as machine learning and deep learning methods, which have been widely adopted across economic and financial domains to support consumers' trading, banking, payments and credit decision-making activities. According to Majeed and Qader (2021), cryptography is a significant area of study because it protects extremely sensitive and secret information against illegal fraud during transmission over the network.

Innovation in blockchain technology is used to combat fraud (Tan, 2021), and it guarantees benefits in the ability to collaborate within the organisation and prove validity and transparency (Kumutha & Jayalakshmi, 2021). It is also used to strengthen the system, preventing cases of fraud to the detriment of AI beneficiaries (Rangone & Busolli, 2021). According to Kumar et al. (2023), blockchain technology offers explainability, privacy and trust in AI-based applications, while AI improves scalability and security while solving the personalisation and governance issues for blockchain-based technologies. This means that AI and blockchain have enormous potential when used together, with AI used to understand, recognise and decide, while blockchain is used to support execution, verification and recording. Weingärtner et al. (2021) proposed the use of blockchain technology to mitigate fraud and prevent malicious human interference.

The importance of big data and AI in the areas of accounting and auditing is indisputable (Agustí & Orta-Pérez, 2023). The implementation of big data technologies in the domain of forensic accounting facilitates the fight against fraud (Mittal et al., 2021). In the transition to a data-driven society, organisations have introduced data-driven algorithms that often apply AI to the real world of fraud detection (van Bruxvoort & van Keulen, 2021). For Delgosha et al. (2021), the most important application of big data is in banks to assist in fraud detection and credit risk analysis.

Fraudulent activities are increasing, and the implementation of a fraud detection method is now considered essential. However, concerns associated with AI have been widely discussed in the literature. Kumar et al. (2023) stated that privacy has become a critical concern because of a series of leaks and misuse of personal data. Grima and Marano (2021) argued that technology is sometimes seen as a disruption that not only offers opportunities for growth and development but also offers opportunities for deception, theft and fraud. According to Webster and Drew (2017), the internet offers the perfect platform for the crime of fraud. The innovative practice of digital payments has caused an increase in the scenario of financial crime (Kurshan & Shen, 2020). Electronic payment methods have led to an increase in various types of fraud in the financial sector, contributing to the substantial spread of fraudulent schemes and causing an increase in global transnational financial crime. Cymru (2006) saw cybercrime as the leveraging of information systems and technology to commit theft, extortion, identity theft, fraud and, in some cases, corporate espionage.

In the literature, several authors have stated that AI has significant implications for auditing. For example, Lamboglia et al. (2021) stated that AI is a useful tool to support accounting management, automate control mechanisms and functions and improve decision-making processes through the production of accounting and performance information in a more efficient way, with the domain of auditing is particularly important in process mining (Rodríguez-Quintero et al., 2021). One of the main steps of the audit is identifying the risk of material misstatement in the financial statements (Zhang, Genga, et al., 2021). Ashtiani and Raahemi (2022) explained that in financial statements, there is manipulation and overvaluation of revenues, assets, sales and profits, while expenses, debts or losses are underestimated. They also noted that the traditional methods used to detect these manipulations are expensive, inaccurate and time-consuming; however, new intelligent methods can be used to assist auditors in analysing financial statements. Nurcahyono et al. (2021) stated that a company's financial ratios are the easiest indicators to detect fraudulent financial statements. In situations in which a company's liquidity and solvency are negative, this will lead to fraud being committed so that the company appears to be performing well.

Based on the foundations of the fraud triangle theory, Aziz and Othman (2021) concluded that awareness and fraud prevention and detection strategies are positively related to the perceived effectiveness of fraud prevention and detection. However, Brazel et al. (2021) found that when warning signs are present in financial statements, directors recognise them and, in turn, have a greater interest in earnings quality. If their concerns are not addressed internally, the auditor externally resolves them (Lando & Shavell, 2004).

Throughout the study, examples of fraud and forms of detection were identified, while in the literature, several meanings of fraud have been highlighted. Fraud is defined as the intentional act of illegal methods or practices for the purpose of obtaining financial gain (Kratcoski, 2018; West & Bhattacharya, 2016). Fraudulent activities vary depending on industry sectors (Al-Hashedi & Magalingam, 2021) and reduce trust in the industry, destabilise economies and affect people's cost of living (West & Bhattacharya, 2016).

Ahmad et al. (2021) stated that investors are misled by distortions, and when fraud is discovered, they make decisions based on overestimated future cash flows, suffering unexpected losses during this period until the correction is completed. According to Tarmidi et al. (2021), investors reacted positively to a company's financial performance, but the amount of fraud in financial information and the way in which it was carried out as well as the auditor's cooperation in these situations raised major questions for investors about a company's financial information.

However, the development of data analysis tools will create benefits in decision-making, validation and audits as well as help accounting students be more productive and better able to collaborate with stakeholders (Islam et al., 2023). Audit reports represent the only information that interested parties have about audits and are conducted using fundamental instruments in economic and financial decision-making (Goicoechea et al., 2021). For Sawangarreerak and Thanathamathee (2021), the identification of fraudulent financial statements helps users to be aware of the occurrence of fraud in financial statements by considering the associated patterns. Objective assessment of evidence is essential for audit effectiveness (Brewster et al., 2021). However, auditors do not evaluate evidence when assessing or addressing the risk of material misstatement due to fraud. Anastasopoulos and Asteriou (2021) explained that there is a dynamic model based on game theory that was proposed to solve the problem of detecting audit fraud under functions of learning effects in the audit process. Koreff et al. (2021) argued that audit data analysis tools adopted by the government promote abuse of power by auditors, enabling politically sensitive processes that encourage the normalisation of behaviour across the sector. Audit committee structure and diversity affect the likelihood of fraud and scandals and the application of sanctions (McLaughlin et al., 2021).

In practice, new trends in AI have brought innovative opportunities to audit procedures in detecting fraud and identifying fraudulent practices in various contexts. In this way, our analysis shows the importance of scientific research on AI trends in auditing and fraud detection to promote innovation, expand knowledge and fill gaps related to the topic.

2.2. Bibliometrics method

A bibliometric review is an easy way to provide information on domains characterised by large amounts of bibliometric and bibliographic information and plays a decisive role in research (Jing et al., 2023). Varma et al. (2021) used this method in their study, and the authors of the current study likewise decided to use this bibliometric method to identify current research trends and interesting topics for future research.

Employing a bibliometric review with a literature review contributes to greater knowledge and a more developed analysis. Despite the similarity between the two research methods, many distinctions are relevant from different perspectives (Pizzi et al., 2021). According to Lamboglia et al. (2021), bibliometric methods are a useful aid in literature reviews even before the start of reading, guiding the researcher to the most influential works and mapping the research field without subjective bias. These methods provide insights into the evolution and intellectual and conceptual structure of a field of research and contribute to a broader understanding of this field of research (Ratzinger-Sakel & Tiedemann, 2022).

According to the literature, bibliometric analysis consists of a set of quantitative techniques used to evaluate published physical units or bibliographic units (Broadus, 1987), providing quantitative performance metrics to evaluate scientific publications in the selected area of study (Bhooshetty, 2023). For Sun et al. (2014), the quantitative study of literature demonstrated in bibliographies provides insight into the growth of literature and how research results are disseminated to readers of papers in a specific field of academic research. The combination of the two methods makes it possible to identify the most influential studies and authors and the existing areas of research interest in this topic (Xu et al., 2018). As Donthu et al. (2021) indicated, bibliometric analysis is useful for deciphering and mapping the cumulative scientific knowledge and evolutionary nuances of well-established fields, making sense of large volumes of unstructured data in a rigorous way.

3. RESEARCH METHODOLOGY AND DATA

This review adopted a mixed approach involving a bibliometric analysis and a literature review. According to Xu et al. (2018), literature reviews aim to map and evaluate the body of literature to identify potential research gaps and highlight the limits of knowledge. Therefore, the decision to evaluate this topic through two alternative research methods was because this approach would contribute with greater knowledge and a more developed analysis of AI trends in auditing and fraud detection. Bibliometric analysis was used to discover emerging trends in article and journal performance, collaboration patterns and research constituents and to explore the intellectual structure of a specific domain in the existing literature. Like Aria and Cucurrulo (2017), the authors followed a five-step research procedure that consisted, first, of defining the research questions and choosing the appropriate bibliometric methods to be able to answer those questions. Second, the database that would be used to export the data was selected. Third, the data was analysed using bibliometric software. Fourth, a decision was made on the best way to visualise the data and use appropriate mapping. Lastly, the findings were interpreted.

Data collection took place in January 2022, and specific criteria were developed to define the results in accordance with the research objectives. Elsevier's Scopus database was used as it is one of the main databases used in research (Pizzi et al., 2021). According to Donthu et al. (2021), the emergence of scientific databases, such as Scopus and Web of Science (WoS), has made it relatively easy to acquire large volumes of bibliometric data that allows the analysis of this data in a very pragmatic way, thus increasing academic interest in analysis bibliometrics in recent times.

The choice of keywords was an integral part of the authors' decision to limit the investigation to studies relevant to the objectives of this research. Given the purpose and objectives of this study, the choice of keywords was purposely restricted to the words "fraud" *or* "artificial intelligence" *or* "audit".

Data cleaning filters were applied, restricting the sample to papers published in the areas of "business, management and accounting" and "informatics" and to papers published in English. We limited the types of article documents searched in the literature, which was chosen as "all open access" and the source type as "newspaper"; no time limit was established for this research.

This research analysed a total of 1,348 papers published from 1986 to 2022 by 3,660 authors (average co-authorship = 3.15) and 538 different journals indexed in the Scopus database. A more detailed description of the types of article documents is presented in Table 1.

Table 1. Statistical analyses of the database

Information about data	*Results*	*Information about data*	*Results*
Time span	[1986, 2022]	Authors	3,660
Sources (journals)	538	Author appearances	4,240
Documents	1,348	Authors of single-authored documents	173
Average years from publication	4,730	Authors of multi-authored documents	3,487
Average citations per document	14,810	Single-authored documents	187
Average citations per year per document	2,112	Documents per author	0,368
References	55,609	Authors per document	2,720
Papers	1,348	Co-authors per document	3,150
Keywords plus (ID)	4,054	Collaboration index	3,000
Author's keywords (DE)	4,057		

The data was saved in the Scopus BibTex (.bib) format to be used later in the bibliometric content analysis platform. First, we installed the latest version of R software (version R-4.1.2). Second, we established the Bibliometrix package (version 3.1) within the R environment to examine and map bibliographic data. Bibliometrix is an R statistical package for analysing and visualising bibliographic data from the WoS and Scopus databases (Derviş, 2019). Aria and Cucurullo (2017) and Derviş (2019) described R as being open source, covering statistical algorithms, mathematical functionalities and visualisation capabilities. This ensures a good bibliometric analysis.

We then used the Bibliometrix functions through the Biblioshiny application developed by Aria and Cuccurullo (2017), which provides a web interface for R Bibliometrix to create descriptive and co-citation networks. The Biblioshiny application stands out as a complete research tool related to Bibliometrics and Scientometrics, having an intuitive interface as well as a wide range of functionalities, analyses and graphics (do Socorro Torres Silva et al., 2022).

In the analysis of outputs of information and content, the top 20 criterion was applied to help understand the relationships between figures, tables, rankings and networks, such as: the 20 most relevant journals with the greatest impact; 20 journals with the most papers published; distribution of papers by the 20 most relevant authors in the research; production distribution and longevity of the 20 most relevant authors in the research; 20 countries with the highest frequency of published papers; and 20 most frequent words in the research. The development of computer technologies and software allowed this methodology to be conducted and positioned as an interesting methodological option to evaluate the structures and networks of science (Gaviria-Marin et al., 2019). According to Pizzi et al. (2021), understanding the scientific impact of a given source is a complex activity due to the high degree of subjectivity that characterises these types of analyses. Therefore, the authors adopted a diversified approach based on a combination of different indicators.

4. BIBLIOMETRIC ANALYSIS RESULTS AND DISCUSSION

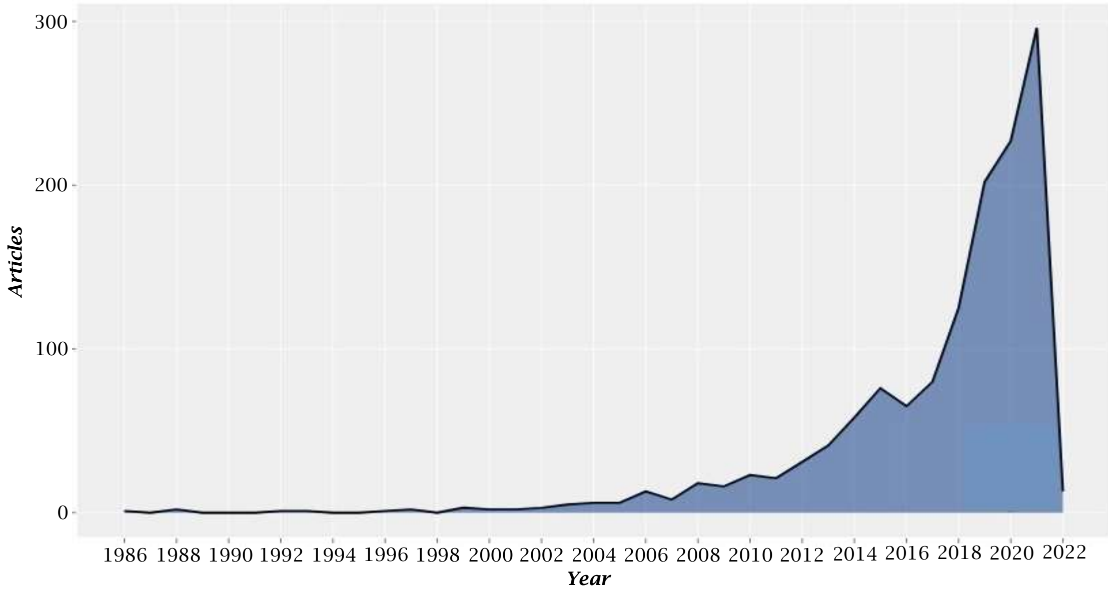
The methodology was subdivided into two complementary analyses. The theoretical analysis was based on a systematic literature review that was based on the most impactful papers that demonstrate AI trends in auditing and fraud detection. This analysis allowed the identification of AI trends and their importance in audit procedures to detect and prevent fraud and, at the same time, mitigate it. It also enlightens readers about the concerns regarding the use of AI in fraudulent and criminal practices.

The empirical analysis is based on a rigorous bibliometric and visualisation tool of a set of database papers from 1986 to 2022 in a set of 1,348 papers on "fraud", "auditing", and "artificial intelligence". This approach allows us to answer a set of indispensable research questions to determine the importance of and need to continue strengthening future research on this topic.

4.1. Papers published in the field of fraud in the areas of AI and auditing

Since 1986, 1,348 papers have been published on fraud, auditing and AI, with papers appearing more frequently since 2002. Figure 1 presents the annual scientific production between 1986 and 2022.

Figure 1. Distribution of the annual scientific production, 1986 to 2022



In Figure 1, the peak in the volume of papers published in the field of fraud in the areas of AI and auditing was achieved in 2021, with 296 papers and an average percentage of citations per paper of 0.85 (mean per year). The analysis reveals that this topic seems to have been relatively unexplored until 2002, probably due to the rapid development of technological resources characterising the last few years. The growth in the number of published papers suggests that this topic is experiencing a phase of great development. Another way to analyse the evolution of papers is through the productivity index.

Responding to *RQ1*, the volume of papers published in the field of fraud in the areas of AI and auditing is 1,348, appearing in 538 different journals from 1986 to January 2022, with a peak of 296 papers in 2021 and an increase in papers occurring from 2002 (Gaviria-Marin et al., 2019). To better understand the evolution of the literature on fraud in the areas of AI and auditing, the literature review identified the increase in papers on fraud, as it is considered a problem that has been increasing and affects people's cost of living and trust in the industry and can destabilise economies (West & Bhattacharya, 2016). The extent of literature on fraud remained stagnant at a relatively low level until 2002. From that year onwards, it began to increase in response to various financial reports and fraud scandals at the turn of the millennium (Ratzinger-Sakel & Tiedemann, 2022). Owusu et al. (2023) stated that the constant increase in the number of searches during this period may be associated with the global financial crisis and the business scandals of 2006 and later years. This change marks another important development of fraud literature and further demonstrates the link between changes in audit procedures and the application of new countermeasures, such as AI, highlighting the increase in scientific research with regard to fraud. AI has a long history, as it was created in 1956 (Huson et al., 2024). Its applicability to auditing and accounting emerged later in specific contexts in all types of procedures, such as combating fraud and irregularities, in the field of criminal justice and regarding the impact of fundamental rights (Castellano, 2021). In recent decades, AI has been a topic of constant debate and evolution, and the literature shows that AI has significant implications in auditing and has also caused significant changes in auditing (Huson et al., 2024).

4.2. Most influential journals in the studied areas

Identifying the journals that publish papers about auditing, AI, and fraud is especially important, not only to determine the papers that should be read and reviewed when carrying out the literature review but also to determine the focus of each journal in these areas for future publication (Rey-Martí et al., 2016). Of the 538 journals verified in the database, the 20 journals with the most published papers show a minimum of 8.00, an average of 19.95 and a standard deviation of 19.52. The journals that are the most prominent in Table 2 are the *Journal of Business Ethics*, with 565 papers, and *The Accounting Review*, with 338 papers. In general, the journals with the most publications are related to the thematic area "business, management and accounting".

Table 2. Journals with the most published papers, 1986 to 2022

Sources	***Papers***
IEEE Access	97
Journal of Financial Crime	35
International Journal of Advanced Computer Science and Applications	33
Journal of Business Ethics	26
Applied Sciences (Switzerland)	24
International Journal of Innovative Technology and Exploring Engineering	23
Mediterranean Journal of Social Sciences	23
Journal of Big Data	16
Computers, Materials and Continua	14
International Journal of Engineering and Advanced Technology	13
Indonesian Journal of Electrical Engineering and Computer Science	12
International Journal of Financial Research	12
Banks and Bank Systems	10
International Journal of Engineering and Technology (UAE)	10
Asian Social Science	9
Lecture Notes in Computer Science (including the subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	9
Risks	9
Complexity	8
Expert Systems with Applications	8
Future Generation Computer Systems	8

Conversely, of the 20 most relevant journals, that is, the ones with the greatest impact, the top one is *IEEE Access*, with a highly significant difference: 97 papers with a great impact, a minimum of 109.00, an average of 214.95, and a standard deviation of 104.62. It is an open-access, peer-reviewed journal published by the Institute of Electrical and Electronics Engineers (IEEE). This journal is related to our research on AI and, in general, the journals that have the greatest impact are connected to the thematic area "computer science". Five of the 20 most relevant journals that the authors had earlier investigated were analysed, which showed that the journal *IEEE Access* had 30 papers in 2020 and reached a peak of 34 papers in 2021. The *International Journal of Advanced Computer Science and Applications* peaked in 2020 with 10 papers, and the journal *Applied Sciences* (Switzerland) peaked in 2021 with 14 papers. However, the *Journal of Financial Crime* and the *Journal of Business Ethics* have a stable number of papers, not varying much or exceeding seven papers per year. Regarding *RQ2* on the most influential journals in these studied areas, it was found that the journals with more published papers are publications in "business, management and accounting". However, the journals with the most impact papers are publications in the field of "computer science".

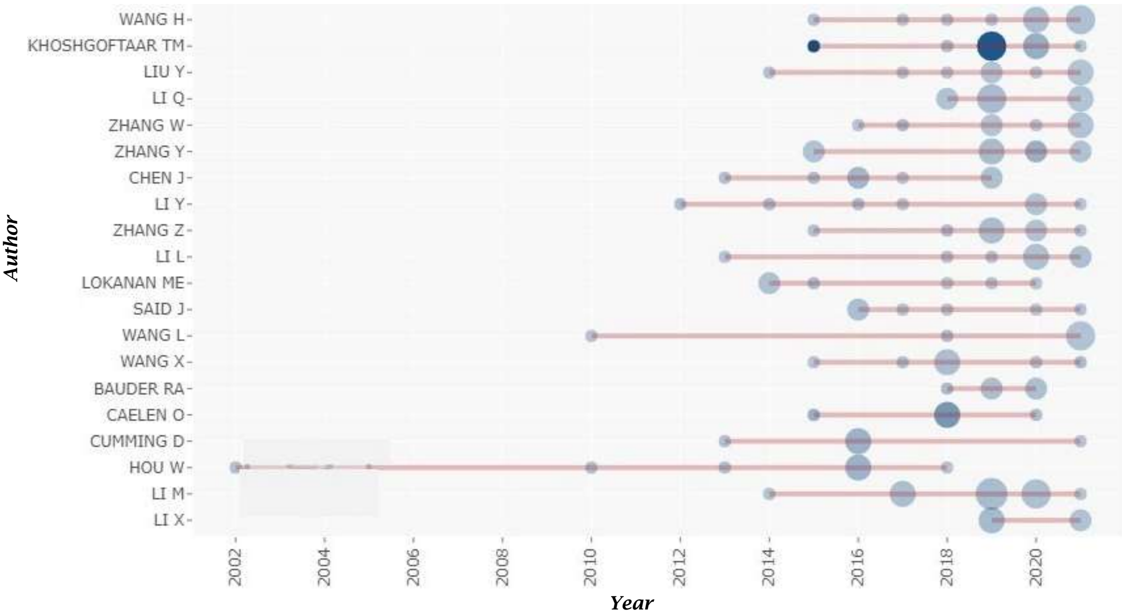
Based on these results and in accordance with the literature, it is possible to reveal that the journals with the greatest impact are in the area of computing due to the emergence of disruptive digital technologies that contribute to significant structural changes in several sectors (Lamboglia et al., 2021). In addition, it is an extremely important tool in accounting and auditing as they are considered knowledge-intensive activities and are highly dependent on information and knowledge management (Agustí & Orta-Pérez, 2023). However, the literature shows that AI is increasingly being used to commit theft, extortion, identity theft, fraud and, in some cases, corporate espionage, making it a critical concern worldwide. The world is moving quickly towards a world full of technology (Nobanee et al., 2023), justifying the result that the highest impact journals are publications in the field of "computer science". The data collection protocol identified that the evolution of this topic occurred in journals such as *IEEE Access, Journal of Financial Crime* and *International Journal of Advanced Computer Science and Applications*, which reinforces the eclectic nature of this research trend.

4.3. Authors with the most publications

According to Merigó and Yang (2017), many authors have made fundamental contributions to the development of research. However, Rey-Martí et al. (2016) stated that the number of citations received by a paper can be verified as being due to the popularity of the author, the paper or the research field and not the relevance of the paper itself. For Danvila-del-Valle et al. (2019), the co-occurrence of authors provides a structure of research communities, and the co-occurrence of citations helps to provide an understanding of the intellectual structure. Of the 1,348 verified papers in the database, the 20 most relevant authors are shown in Figure 2, with the most prominent authors being Wang, H. and Khoshgoftaar, T. M. both of whom started publishing in 2015. Wang, H. appeared 11 times and Khoshgoftaar, T. M. appeared 10 times. Of the top 20 papers created for this analysis, the minimum is 7.00, the average is 9.75 and the standard deviation is 4.61 papers. This finding is very logical for this research as papers by these authors are usually published in the main journals and receive more attention from the scientific community (Martínez-López et al., 2018).

The authors who stand out in terms of production and longevity are Chen, J. and Hou, W., as can be seen in Figure 2. Chen, J. started publishing in 2013 with one publication and ended in 2019 with two publications. Hou, W. started publishing earlier, in 2002, and he achieved three publications in 2016 and ended in 2018 with one publication. Of the top 20 papers created for this analysis, the minimum is 5.00, the average is 6.75, and the standard deviation is 1.73. The transition from the 2010s to the 2020s marked the blossoming of the research careers of other authors, who have since maintained a higher level of publications, as is the case for Caelen, O., who started publishing in 2015 and ended in 2020, and Cumming, D., who published first in 2013 and finally in 2021.

Figure 2. Distribution of the production and the longevity of the 20 most relevant authors, 1986 to 2022



Regarding the publications by country, there are two situations. First, authors who publish alone or with authors from the same country (single-country publication — SCP) and authors who collaborate with authors from other countries to publish works (multiple-country publication — MCP). Thus, the initial database, China, the United States of America (USA), and the United Kingdom (UK) are the countries that published most in an SCP situation. In the case of China, out of 129 papers, 97 were SCP and 32 were MCP. Of the 121 papers published in the USA, 91 appeared in an SCP, and 30 were MCP. Of the UK's 69 papers, 40 were SCP and 29 were MCP. However, in general, papers are most often in the form of an SCP: for the top 20 papers identified for this analysis, the minimum is 12.00, the average is 37.75 and the standard deviation is 32.37.

It was found that the publication trend of a single country has more frequency than publications that involve more countries. According to the literature analysis, this has to do with the uncertainty of the factors that determine the probability of fraud, fraud detection, and the application of AI (Tang & Karim, 2019). According to Owusu et al. (2023), fraud theory encompasses the personal characteristics and abilities of individuals that play a significant role in the occurrence of fraud. Bierstaker (2009) explained that cultural differences are significantly related to different perceptions of the seriousness of a range of fraudulent activities, including corruption. For example, accountants in the Asia-Pacific region do not take bribes or illegal gratuities as seriously as accountants in other geographic areas. Thus, it is possible to justify the tendency for papers from a single country that have more frequency than papers with more countries involved.

Of the 1,348 papers in the database, among the 20 countries with the highest frequency of published papers, as can be seen in Table 3, the top countries are the USA with 404 papers, followed by China with 320 papers and the UK with 232 papers. However, both the USA and China are countries with high population density.

Countries around the world have made substantial contributions to AI, auditing, and fraud, most notably the USA and China. On the one hand, just as Huson et al. (2024) state, these nations have a substantial presence in the technology sector, with many cutting-edge technology companies and research institutes based there. Many of the major players in the AI sector, such as Google, Microsoft, and International Business Machines (IBM), are based in the USA and China. On the other hand, the USA is the continent with the most cases of fraud (Association of Certified Fraud Examiners [ACFE], 2024) and the economies of countries such as the USA and China have become increasingly interconnected (Bierstaker, 2009).

Table 3. Country scientific production

Country	*Papers*
USA	404
China	320
UK	232
India	172
Malaysia	116
Indonesia	96
Germany	91
Spain	91
Italy	89
Australia	88
France	72
Canada	57
South Korea	53
Netherlands	47
Brazil	44
Nigeria	44
Saudi Arabia	44
Pakistan	41
South Africa	36
Türkiye	33

Regarding the *RQ3*, based on the authors with more publications on this topic and the countries of publication, it was found that the authors with the greatest relevance are Wang, H. and Khoshgoftaar, T. M., and the authors who stand out in terms of longevity in publications are Chen, J. and

Hou, W. The countries that are prominent in terms of the number of publications are the USA, China, and the UK.

4.4. Most repeated words in papers

Of the 1,348 papers in the database, an analysis was performed on the 4,054 keywords, allowing the identification of groups of competing words and the relationships between them. On the one hand, the author's keywords refer to those that are generally used to identify the topic of the paper (Bermeo-Giraldo et al., 2021), On the other hand, keywords are assigned by authors and keyword competition shows how often they appear alongside others in published documents (Gaviria-Marin et al., 2018). The network of keywords grouped by the authors shows a total of 50 different terms grouped into four different clusters. The predominant keyword is "crime", with a 13% ranking. It is linked to 16 other keywords within the same theme, including fraud and AI. The second cluster has a total of 10 keywords, with the word "data mining" standing out with a 4.2% ranking. The third cluster has a total of 12 interconnected keywords, and the term that is the most prominent is "learning systems", with a 4.3% ranking. Finally, in the fourth cluster, which contains a total of 11 interconnected keywords, the word that stands out the most is "network security", with a ranking of 2.1%. The ranking referred to in this analysis is the ratio of the number of papers to the number of citations, in accordance with Merigó and Yang (2017).

The shape of the bibliographic coupling map shows how the research trend is evolving towards groups of more related works. As Lamboglia et al. (2021) explained in their study, this analysis is based on the use of keyword co-occurrence networks, and the papers mentioned in each cluster identified the connections between the keywords; however, an article could use two or more of these keywords, which is considered a limitation in the analysis.

A content analysis was undertaken through a literature review to obtain insights into each cluster and to identify the research subtopics within each of the four clusters identified from the keyword analysis. Donthu et al. (2021) argued that the larger the node, the greater the occurrence of the keyword, and the thicker the link between nodes, the greater the occurrence of co-occurrences between keywords. Each group represents a thematic cluster, and the nodes and links of that cluster can be used to explain the topic coverage (cluster) and the relationships (links) between the topics (nodes) that manifest under that theme (cluster). Based on their connections, it is possible to recognise four clusters:

1. The first cluster focuses on crime and presents the following links: fraud detection; computer crime, electronic commerce; AI; fraud, social networking; malware; marketing; Internet; surveys; online systems; sales; websites; and algorithms.
2. The second cluster focuses on data mining and has the following connections: anomaly detection; risk assessment; intrusion detection; big data; behavioural research; statistics; decision-making; information management; and clustering algorithms.
3. The third cluster focuses on learning systems and presents the following connections: classification (of information); decision trees; deep learning; support vector machines; finance; learning algorithms; machine learning; feature extraction; neural networks; credit card fraud detections; fraudulent transactions; and large datasets.
4. The fourth cluster focuses on network security and presents the following connections: authentication; blockchain; security of data; cryptography; insurance; human; security; access control; biometrics; and humans.

When analysing the connections between keywords, it appears that the most recurrent keywords are crime, data mining, learning systems and network security. Therefore, it is interesting to understand the transversality of the themes covered by these journals. However, there are several trends in AI as a complement both to the commission of crimes and in the way of detecting and mitigating them.

Two different analyses were performed to identify the most repeated words, one from the perspective of the analysis of the most repeated words in the 1,348 papers and the other from the perspective of the keywords chosen by the authors. Of the top 20 papers identified for this analysis, the minimum is 28.00, the average is 49.90 and the standard deviation is 43.16. As can be seen in Table 4, of the 10 most frequent words, the word "crime" is the most cited, with a total of 23 occurrences, followed by "fraud detection" with 75 and "data mining" with 59. Of the most frequent keywords, the words "fraud" with 153 occurrences, "fraud detection" with 117 occurrences, and "machine learning", with 82 occurrences, are used most often.

Table 4. Most frequent words in papers

Keywords	*Papers*
crime	231
fraud detection	75
data mining	59
learning systems	58
classification (of information)	52
anomaly detection	44
decision trees	40
deep learning	39
network security	39
support vector machines	37
fraud	153
fraud detection	117
machine learning	82
blockchain	53
anomaly detection	43
data mining	43
deep learning	40
security	38
big data	27
classification	26

The analysis of keywords and author's keywords is an analysis of qualitative word frequency, knowing that the data appears with greater frequency, as presented in Figure 3. Heimerl et al. (2014) detailed that word clouds are used to provide an intuitive and visually appealing overview of a text to describe the words that most frequently occur within a text and to help judge whether they are relevant to a specific information need. Based on this analysis, it was found that the most repeated words in the papers are "crime", "fraud detection" and "data mining". However, the most used keywords were "fraud", "fraud detection" and "machine learning". The analysis performed on keywords recognises the extremely widespread subjects covered by the bibliometric analysis (Ellegaard & Wallin, 2015).

Figure 3. Word cloud keywords and word cloud authors' keywords

AI is increasingly used in the scientific area of auditing and in detecting fraud due to unusual circumstances and anomalies that may indicate fraudulent procedures. According to Nobanee et al. (2023), information technology crimes and financial crimes are two closely related phenomena that have become increasingly prevalent in today's digital era, which highlights the fact that both criminal activities committed using digital technologies and financial crime refer to illegal activities that aim to obtain financial gains through deception, fraud or other unethical means. This relationship is complex and multifaceted, and both use AI as a resource. Therefore, the results and the literature review show that there are great concerns about crime and the way it is committed as well as interest in creating mechanisms to detect and combat crime using AI.

5. CONCLUSION

This research draws conclusions about AI trends in auditing and fraud detection by taking a mixed approach involving a bibliometric analysis and a literature review. This allows us to fill in the gaps, as there has been no specific research on AI trends in auditing and fraud detection and, therefore, no such research contributes to scientific knowledge. The originality of this research lies in its mixed approach involving a bibliometric analysis and a literature review, which provides greater knowledge and a more developed analysis of AI trends in auditing and fraud detection.

The findings demonstrate that the evolution of technology in recent years has created audit mechanisms and tools with positive effects in terms of improving and facilitating procedures to combat fraud and irregularities in the field of criminal justice and fundamental rights. Regarding auditing to combat fraud, it was found based on a set of information referred to in the literature that the use of traditional methods to identify fraud, including audits and manual inspections, is expensive, inaccurate and time-consuming. AI-enabled intelligent methods can significantly aid auditors' analyses and inspections. In conclusion, new AI trends have affected citizen behaviour as well as business and financial development.

The data was collected from Elsevier's Scopus database and the bibliometric analysis was conducted using the R Bibliometrix software, which allowed the analysis of a total of 1,348 papers published from 1986 to 2022 by 3,660 authors. The results reveal that the research trend began to increase in 2002, especially in 2021, with a peak of 296 papers; *IEEE Access* and the *Journal of Financial Crime* published a significant number of papers; and Wang, H. was the most productive author. The USA produced a considerable body of work related to AI research, auditing and fraud, with 404 papers. From among the 1,348 papers, 4,054 keywords were analysed, allowing the identification of four groups of competing words and the relationships between them. The results indicate that the most recurrent keywords used are crime, data mining, learning systems and network security. This confirms the growing academic interest in this research topic, especially in recent years, and reveals a great concern in the various trends of AI in both the practice of crimes and in how crimes are detected and mitigated. By analysing keywords and author keywords through word frequency from our dataset, it is possible to identify groups of papers that examine the links between "crime", "fraud detection" and "data mining" from different points of view.

Based on the analysis, it was possible to identify gaps in studies relating to the relationship between AI trends in auditing and fraud detection. Although there are bibliometric analyses on AI, auditing and fraud, they remain limited as they are found in individual analyses and in different contexts. Furthermore, the literature does not provide models that support auditing in detecting fraud through AI. Future research should consider this gap to provide mechanisms to support fraud detection.

This research draws relevant information from the literature review, confirming the various mechanisms developed through AI to help detect fraud in various areas. The creation of innovative AI tools to combat the most diverse fraud, corruption and economic crimes is increasingly important. These technological innovations increase the ethical motivations for deterring fraud, and consequently, these changes will allow a long-term decrease in the incidence of fraud. The literature review also reveals a growing concern about the use of AI in fraudulent and criminal practices.

This research presents two limitations. First, the difficulty of the bibliometric approach was apparent, as it reports research with a vast set of data with results that change depending on the choices that are made, specifically the choice of the database on which the research is based. If a database other than Scopus was chosen, a different set of search terms could generate different groupings, resulting in different interpretations. Second, there is a lack of literature that demonstrates the importance of new AI trends in audit procedures in fraud detection through bibliometric analysis, but this scientific research is crucial to promoting innovation and expanding knowledge in these areas.

This research has theoretical and practical implications. The theoretical implications are the contributions to the literature by providing useful information on AI trends in auditing and fraud detection. These implications provide a starting point for researchers interested in studying this research topic with an innovative methodology. The evidence obtained allows the development of professional judgment to contribute to a better understanding of the current state of research and to provide valuable information for future research efforts and decision-making in the area. The practical implications of this research evaluate new trends in AI in auditing and fraud detection as well as the malicious use of AI in fraud and the impacts caused by these uses. It also shows the implications for auditors of AI trends to improve the efficiency and effectiveness of their procedures in detecting fraud.

The authors propose as a future development that a broader analysis be conducted with other journal databases to expand the results of this research.

REFERENCES

Agustí, M. A., & Orta-Pérez, M. (2023). Big data and artificial intelligence in the fields of accounting and auditing: A bibliometric analysis. *Spanish Journal of Finance and Accounting*, *52*(3), 412–438. https://doi.org/10.1080/02102412.2022.2099675

Ahmad, S. R., Senan, N. A. M., Ali, I., Ali, K., Khan, I. A., & Baig, A. (2021). Investor reaction to the discovery of accounting fraud: The period from the discovery of the fraud to the completion of the correction. *Academic Journal of Interdisciplinary Studies*, *10*(6), 171–190. https://doi.org/10.36941/ajis-2021-0163

Al-Hashedi, K. G., & Magalingam, P. (2021). Financial fraud detection applying data mining techniques: A comprehensive review from 2009 to 2019. *Computer Science Review*, *40*, Article 100402. https://doi.org/10.1016/j.cosrev.2021.100402

Anastasopoulos, N., & Asteriou, D. (2021). Optimal dynamic auditing based on game theory. *Operational Research*, *21*, 1887–1912. https://doi.org/10.1007/s12351-019-00491-3

Aria, M., & Cuccurullo, C. (2017). Bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Ashtiani, M. N., & Raahemi, B. (2022). Intelligent fraud detection in financial statements using machine learning and data mining: A systematic literature review. *IEEE Access*, *10*, 72504–72525. https://doi.org/10.1109/ACCESS.2021.3096799

Association of Certified Fraud Examiners (ACFE). (2024). *Occupational fraud 2024: A report to the nations.* https://legacy.acfe.com/report-to-the-nations/2024/

Aziz, F. L. A., & Othman, I. W. (2021). Internal auditors' perception on the efficacy of fraud prevention and detection in the public sector. *Universal Journal of Accounting and Finance*, *9*(4), 764–772. https://doi.org/10.13189/ujaf.2021.090422

Bermeo-Giraldo, M. C., Grajales-Gaviria, D., Valencia-Arias, A., & Palacios-Moya, L. (2021). Evolución de la producción científica sobre el fraude contable en las organizaciones: Análisis bibliométrico [Evolution of scientific production on accounting fraud in organizations: Bibliometric analysis]. *Estudios Gerenciales*, *37*(160), 492–505. https://doi.org/10.18046/j.estger.2021.160.4000

Bhooshetty, L. (2023) Rejuvenating human resource accounting research: A review using bibliometric analysis. *Management Review Quarterly*. https://doi.org/10.1007/s11301-023-00357-1

Bierstaker, J. L. (2009). Differences in attitudes about fraud and corruption across cultures: Theory, examples, and recommendations. *Cross Cultural Management: An International Journal*, *16*(3), 241–250. https://doi.org/10.1108/13527600910977337

Brazel, J. F., Lucianetti, L., & Schaefer, T. J. (2021). Reporting concerns about earnings quality: An examination of corporate managers. *Journal of Business Ethics*, *171*, 435–457. https://doi.org/10.1007/s10551-020-04436-1

Brewster, B. E., Johanns, A. J., Peecher, M. E., & Solomon, I. (2021). Do stronger wise-thinking dispositions facilitate auditors' objective evaluation of evidence when assessing and addressing fraud risk? *Contemporary Accounting Research*, *38*(3), 1679–1711. https://doi.org/10.1111/1911-3846.12684

Broadus, R. N. (1987). Toward a definition of "bibliometrics". *Scientometrics*, *12*, 373–379. https://doi.org/10.1007/BF02016680

Castellano, P. S. (2021). Inteligencia artificial y administración de Justicia: ¿Quo vadis, justitia? [Artificial intelligence and administration of justice: Quo vadis, justitia?]. *Revista de Internet, Derecho y Política, 33*. https://doi.org/10.7238/idp.v0i33.373817

Cymru, T. (2006). Cybercrime: An epidemic: Who commits these crimes, and what are their motivations? *Queue*, *4*(9), 24–35. https://doi.org/10.1145/1180176.1180190

Danvila-del-Valle, I., Estévez-Mendoza, C., & Lara, F. J. (2019). Human resources training: A bibliometric analysis. *Journal of Business Research*, *101*, 627–636. https://doi.org/10.1016/j.jbusres.2019.02.026

de Vos, M., & Pouwelse, J. (2021). ConTrib: Maintaining fairness in decentralized big tech alternatives by accounting work. *Computer Networks*, *192*, Article 108081. https://doi.org/10.1016/j.comnet.2021.108081

Delgosha, M. S., Hajiheydari, N., & Fahimi, S. M. (2021). Elucidation of big data analytics in banking: A four-stage Delphi study. *Journal of Enterprise Information Management*, *34*(6), 1577–1596. https://doi.org/10.1108/JEIM-03-2019-0097

Derviş, H. (2019). Bibliometric analysis using Bibliometrix an R package. *Journal of Scientometric Research*, *8*(3), 156–160. https://doi.org/10.5530/jscires.8.3.32

do Socorro Torres Silva, M., de Oliveira, V. M., & Correia, S. E. N. (2022). Mapeamento científico na Scopus com o Biblioshiny: Uma análise bibliométrica das tensões organizacionais [Scientific mapping in Scopus with Biblioshiny: A bibliometric analysis of organizational tensions]. *Contextus — Revista Contemporânea de Economia e Gestão*, *20*, 54–71. ttps://doi.org/10.19094/contextus.2022.72151

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Ellegaard, O., & Wallin, J. A. (2015). The bibliometric analysis of scholarly production: How great is the impact? *Scientometrics*, *105*, 1809–1831. https://doi.org/10.1007/s11192-015-1645-z

Gaviria-Marin, M., Merigó, J. M., & Baier-Fuentes, H. (2019). Knowledge management: A global examination based on bibliometric analysis. *Technological Forecasting and Social Change*, *140*, 194–220. https://doi.org/10.1016/j.techfore.2018.07.006

Gaviria-Marin, M., Merigó, J. M., & Popa, S. (2018). Twenty years of the Journal of Knowledge Management: A bibliometric analysis. *Journal of Knowledge Management*, *22*(8), 1655–1687. https://doi.org/10.1108/JKM-10-2017-0497

Goicoechea, E., Gómez-Bezares, F., & Ugarte, J. V. (2021). Improving audit reports: A consensus between auditors and users. *International Journal of Financial Studies*, *9*(2), Article 25. https://doi.org/10.3390/ijfs9020025

Grima, S., & Marano, P. (2021). Designing a model for testing the effectiveness of a regulation: The case of DORA for insurance undertakings. *Risks*, *9*(11), Article 206. https://doi.org/10.3390/risks9110206

Hashimzade, N., Huang, Z., & Myles, G. D. (2010). Tax fraud by firms and optimal auditing. *International Review of Law and Economics, 30*(1), 10–17. https://doi.org/10.1016/j.irle.2009.08.002

Heimerl, F., Lohmann, S., Lange, S., & Ertl, T. (2014). Word cloud explorer: Text analytics based on word clouds. In *Proceedings of the 2014 47th Hawaii International Conference on System Sciences* (pp. 1833–1842). https://doi.org/10.1109/HICSS.2014.231

Huson, Y. A., Sierra-García, L., & Garcia-Benau, M. A. (2024). A bibliometric review of information technology, artificial intelligence, and blockchain on auditing. *Total Quality Management & Business Excellence*, *35*(1–2), 91–113. https://doi.org/10.1080/14783363.2023.2256260

Islam, M. S., Farah, N., & Wang, T. (2023). Accounting data analytics in R: A case study using Tidyverse. *Journal of Emerging Technologies in Accounting, 20*(2), 243–250. https://doi.org/10.2308/JETA-2021-023

Jacob, M., & Meek, V. L. (2013). Scientific mobility and international research networks: Trends and policy tools for promoting research excellence and capacity building. *Studies in Higher Education*, *38*(3), 331–344. https://doi.org/10.1080/03075079.2013.773789

Jing, Y., Wang, C., Chen, Y., Wang, H., Yu, T., & Shadiev, R. (2023). Bibliometric mapping techniques in educational technology research: A systematic literature review. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-12178-6

Karpoff, J. M. (2021). The future of financial fraud. *Journal of Corporate Finance*, *66*, Article 101694. https://doi.org/10.1016/j.jcorpfin.2020.101694

Koreff, J., Weisner, M., & Sutton, S. G. (2021). Data analytics (ab) use in healthcare fraud audits. *International Journal of Accounting Information Systems*, *42*, Article 100523. https://doi.org/10.1016/j.accinf.2021.100523

Kowal-Pawul, A., & Przekota, G. (2021). Importance of VAT digitization for income disclosure in section F-construction — A case for Poland. *Journal of International Studies*, *14*(4), 67–86. https://doi.org/10.14254/2071-8330.2021/14-4/5

Kratcoski, P. C. (2018). Introduction: Overview of major types of fraud and corruption. In P. C. Kratcoski & M. Edelbacher (Eds.), *Fraud and corruption: Major types, prevention, and control* (pp. 3–19). Springer. https://doi.org/10.1007/978-3-319-92333-8_1

Kumar, S., Lim, W. M., Sivarajah, U., & Kaur, J. (2023). Artificial intelligence and blockchain integration in business: Trends from a bibliometric-content analysis. *Information Systems Frontiers*, *25*, 871–896. https://doi.org/10.1007/s10796-022-10279-0

Kumutha, K., & Jayalakshmi, S. (2021). The impact of the blockchain on academic certificate verification system-review. *EAI Endorsed Transactions on Energy Web*, *8*(36), Article e11. http://doi.org/10.4108/eai.29-4-2021.169426

Kurshan, E., & Shen, H. (2020). Graph computing for financial crime and fraud detection: Trends, challenges, and outlook. *International Journal of Semantic Computing*, *14*(4), 565–589. https://doi.org/10.1142/S1793351X20300022

Lamboglia, R., Lavorato, D., Scornavacca, E., & Za, S. (2021). Exploring the relationship between audit and technology. A bibliometric analysis. *Meditari Accountancy Research*, *29*(5), 1233–1260. https://doi.org/10.1108/MEDAR-03-2020-0836

Lando, H., & Shavell, S. (2004). The advantage of focusing law enforcement effort. *International Review of Law and Economics, 24*(2), 209–218. https://doi.org/10.1016/j.irle.2004.08.005

Laufs, J., & Borrion, H. (2022). Technological innovation in policing and crime prevention: Practitioner perspectives from London. *International Journal of Police Science & Management*, *24*(2), 190–209. https://doi.org/10.1177/14613557211064053

Majeed, A. A., & Qader, B. A. (2021). An improved Vigener algorithm based on circular-left-shift key and MSB binary for data security. *Indonesian Journal of Electrical Engineering and Computer Science*, *23*(1), 431–437. http://doi.org/10.11591/ijeecs.v23.i1.pp431-437

Martínez-López, F., Merigó, J., Valenzuela-Fernández, L., & Nicolás, C. (2018). Fifty years of the European Journal of Marketing: A bibliometric analysis. *European Journal of Marketing*, *52*(1–2), 439–468. https://doi.org/10.1108/EJM-11-2017-0853

McLaughlin, C., Armstrong, S., Moustafa, M. W., & Elamer, A. A. (2021). Audit committee diversity and corporate scandals: Evidence from the UK. *International Journal of Accounting & Information Management*, *29*(5), 734–763. https://doi.org/10.1108/IJAIM-01-2021-0024

Merigó, J. M., & Yang, J.-B. (2017). A bibliometric analysis of operations research and management science. *Omega*, *73*, 37–48. https://doi.org/10.1016/j.omega.2016.12.004

Mittal, P., Kaur, A., & Gupta, P. K. (2021). The mediating role of big data to influence practitioners to use forensic accounting for fraud detection. *European Journal of Business Science and Technology*, *7*(1), 47–58. https://doi.org/10.11118/ejobsat.2021.009

Mutschmann, M., Hasso, T., & Pelster, M. (2022). Dark triad managerial personality and financial reporting manipulation. *Journal of Business Ethics*, *181*, 763–788. https://doi.org/10.1007/s10551-021-04959-1

Nicholls, J., Kuppa, A., & Le-Khac, N.-A. (2021). Financial cybercrime: A comprehensive survey of deep learning approaches to tackle the evolving financial crime landscape. *IEEE Access*, *9*, 163965–163986. https://doi.org/10.1109/ACCESS.2021.3134076
Nobanee, H., Alodat, A., Bajodah, R., Al-Ali, M., & Al Darmaki, A. (2023). Bibliometric analysis of cybercrime and cybersecurity risks literature. *Journal of Financial Crime*, *30*(6), 1736–1754. https://doi.org/10.1108/JFC-11-2022-0287
Nurcahyono, N., Hanum, A. N., Kristiana, I., & Pamungkas, I. D. (2021). Predicting fraudulent financial statement risk: The testing Dechow f-score financial sector company in Indonesia. *Universal Journal of Accounting and Finance, 9*(6), 1487–1494. https://doi.org/10.13189/ujaf.2021.090625
Nurkey, A., Kosherbayeva, A., Yedilkhan, D., & Kuandykov, N. (2021). Corruption prevention based on the principal-agent approach and game theory using ICT: The case study of Kazakhstan. *Public Policy and Administration*, *20*(4), 530–542. https://doi.org/10.13165/VPA-21-20-4-13
Owusu, G. M. Y., Koomson, T. A. A., & Donkor, G. N. A. (2023). A scientometric analysis of the structure and trends in corporate fraud research: A 66-year review. *Journal of Financial Crime, 31*(3), 629–651. https://doi.org/10.1108/JFC-05-2023-0121
Pizzi, S., Venturelli, A., Variale, M., & Macario, G. P. (2021). Assessing the impacts of digital transformation on internal auditing: A bibliometric analysis. *Technology in Society*, *67*, Article 101738. https://doi.org/10.1016/j.techsoc.2021.101738
Rangone, A., & Busolli, L. (2021). Managing charity 4.0 with blockchain: A case study at the time of COVID-19. *International Review on Public and Nonprofit Marketing*, *18*, 491–521. https://doi.org/10.1007/s12208-021-00281-8
Ratzinger-Sakel, N. V. S., & Tiedemann, T. (2022). Fraud in accounting and audit research (1926–2019) — A bibliometric analysis. *Accounting History Review*, *32*(2–3), 97–143. https://doi.org/10.1080/21552851.2022.2143827
Rey-Martí, A., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2016). A bibliometric analysis of social entrepreneurship. *Journal of Business Research*, *69*(5), 1651–1655. https://doi.org/10.1016/j.jbusres.2015.10.033
Rodríguez-Quintero, J.-F., Sánchez-Díaz, A., Iriarte-Navarro, L., Maté, A., Marco-Such, M., & Trujillo, J. (2021). Fraud audit based on visual analysis: A process mining approach. *Applied Sciences*, *11*(11), Article 4751. https://doi.org/10.3390/app11114751
Sánchez, M., Olmedo, V., Narvaez, C., Hernández, M., & Urquiza-Aguiar, L. (2021). Generation of a synthetic dataset for the study of fraud through deep learning techniques. *International Journal on Advanced Science, Engineering, and Information Technology*, *11*(6), 2534–2542. https://ijaseit.insightsociety.org/index.php/ijaseit/article/view/14345
Sawangarreerak, S., & Thanathamathee, P. (2021). Detecting and analyzing fraudulent patterns of financial statement for open innovation using discretization and association rule mining. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(2), Article 128. https://doi.org/10.3390/joitmc7020128
Subramanian, S., Billsberry, J., & Barrett, M. (2023). A bibliometric analysis of person-organization fit research: Significant features and contemporary trends. *Management Review Quarterly*, *73*, 1971–1999. https://doi.org/10.1007/s11301-022-00290-9
Sun, X., Tang, W., Ye, T., Zhang, Y., & Zhang, L. (2014). Integrated care: A comprehensive bibliometric analysis and literature review. *International Journal of Integrated Care*, *14*(6). https://doi.org/10.5334/ijic.1659
Tan, T. (2021). Intelligent application of artificial intelligence internet of things technology in the economic and legal fields. *Mobile Information Systems*, Article 3118733. https://doi.org/10.1155/2021/3118733
Tang, J., & Karim, K. E. (2019). Financial fraud detection and big data analytics — Implications on auditors' use of fraud brainstorming session. *Managerial Auditing Journal*, *34*(3), 324–337. https://doi.org/10.1108/MAJ-01-2018-1767
Tarmidi, D., Murwaningsari, E., & Ahnan, Z. M. (2021). Earnings quality and audit quality: Analysis of investor reaction. *Humanities and Social Sciences Letters*, *9*(3), 250–225. https://doi.org/10.18488/journal.73.2021.93.250.259
van Bruxvoort, X., & van Keulen, M. (2021). Framework for assessing ethical aspects of algorithms and their encompassing socio-technical system. *Applied Sciences*, *11*(23), Article 11187. https://doi.org/10.3390/app112311187
Varma, A., Piedepalumbo, P., & Mancini, D. (2021). Big data and accounting: A bibliometric study. *The International Journal of Digital Accounting Research*, *21*, 203–238. https://doi.org/10.4192/1577-8517-v21_8
Weber, P., Carl, K. V., & Hinz, O. (2024). Applications of explainable artificial intelligence in Finance — A systematic review of finance, information systems, and computer science literature. *Management Review Quarterly*, *73*, 867–907. https://doi.org/10.1007/s11301-023-00320-0
Webster, J., & Drew, J. M. (2017). Policing advance fee fraud (AFF): Experiences of fraud detectives using a victim-focused approach. *International Journal of Police Science & Management*, *19*(1), 39–53. https://doi.org/10.1177/1461355716681810
Weingärtner, T., Batista, D., Köchli, S., & Voutat, G. (2021). Prototyping a smart contract based public procurement to fight corruption. *Computers*, *10*(7), Article 85. https://doi.org/10.3390/computers10070085
West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. *Computers & Security*, *57*, 47–46. https://doi.org/10.1016/j.cose.2015.09.005
Xu, X., Chen, X., Jia, F., Brown, S., Gong, Y., & Xu, Y. (2018). Supply chain finance: A systematic literature review and bibliometric analysis. *International Journal of Production Economics*, *204*, 160–173. https://doi.org/10.1016/j.ijpe.2018.08.003
Zhang, L., Zhang, W., McNeil, M. J., Chengwang, N., Matteson, D. S., & Bogdanov, P. (2021). AURORA: A unified framework for anomaly detection on multivariate time series. *Data Mining and Knowledge Discovery*, *35*, 1882–1905. https://doi.org/10.1007/s10618-021-00771-7
Zhang, S., Genga, L., Yan, H., Nie, H., Lu, X., & Kaymak, U. (2021). Towards multi-perspective conformance checking with fuzzy sets. *International Journal of Interactive Multimedia and Artificial Intelligence*, *6*(5), 134–141. https://doi.org/10.9781/ijimai.2021.02.013