History of accounting research on Artificial Intelligence applications (1984-2023): a bibliometric analysis

Dott. RICCARDO CAMILLI - Prof. ALESSANDRO MECHELLI - Prof. IVO HRISTOV

ABSTRACT: ***(HISTORY OF ACCOUNTING RESEARCH ON ARTIFICIAL INTELLIGENCE APPLICATIONS (1984-2023): A BIBLIOMETRIC ANALYSIS):*** *In tracing the evolution of accounting research, this paper delves into the historical landscape of Artificial Intelligence (AI)-based applications, examining their transformative impact on accounting practices throughout the annals of time. The study utilizes a bibliometric analysis, employing two bibliometric software (i.e., Bibliometrix and VosViewer) as analytical tools. The methodological approach involves a multifaceted process, including a review of relevant literature on AI, extraction of key AI application keywords, Scopus-based search for English articles in accounting journals, and subsequent analysis of the 378 collected articles using the two bibliometric software. Our analysis uncovers a significant timeline in the evolution of AI in accounting, as marked by pivotal moments and transformative applications. Rooted in Turing's 1950 proposition, AI faced funding constraints until the emergence of business-specific AI systems in the 1980s. Despite steady growth until the late 2010s, limitations in accounting applications persisted. The late 2010s witnessed a seismic shift with disruptive AI applications reshaping accounting practices, including Deep Learning (DL) and Machine Learning (ML). Challenges arose in AI integration within auditing, highlighting nuanced judgment requirements. Recent advancements liberated auditors from manual tasks via AI, big data analytics, and robotics, yet raised ethical and social accountability concerns. Financial reporting analysis evolved with AI-driven predictive modeling and risk identification in textual disclosures. This evolutionary journey emphasizes guidance for present and future accounting researchers, practitioners and policy makers. Thus, researchers should explore beyond Neural Networks (NNs), focus on disruptive tech like ML, DL, and Robotic Process Automation (RPA) for auditing and financial analysis, deepen opportunities and implications around text mining of narrative financial disclosures, conduct longitudinal studies on innovation of single accounting practices, and delve into the ethical implications of AI-based applications. Professionals should foster collaborations, adapt skills to advanced tools, and assess AI-based application swithin organizations. Policymakers should promote continuous education initiatives, address ethical concerns, and emphasize transparent, fair AI decision-making algorithms for accounting practices.*

KEYWORDS: Accounting, Artificial Intelligence, Bibliometric analysis
DOI: 10.17408/RIREARCAMIH010203042024 – ISSN 1593-9154
Ricevuto: 22-01-2024 - Accettato: 06-05-2024

1. Introduction

Artificial Intelligence (AI), through its several applications, has increased the number of activities to carry out and it is nowadays gaining the centre of debates among researchers of various disciplines (WANG et al., 2023). AI is even carrying out a substantial amount of accounting practices (SUTTON et al., 2016), from the simplest (i.e., automatic extraction of relevant information from invoices) to the most complex (i.e., prediction of corporate bankruptcy through empirically-based models) (MARCELLO and CAFARO, 2020). This substantial use of AI applications in carrying out accounting practices is motivated by severalfactors. For instance, given that accounting practices are carried out by humans (NØRREKLIT et al., 2010), and all humans are affected by limited rationality (SIMON, 1947), AI can offer a recognized valuable support to increase rationality in their judgments and decisions (ATHOTA et al., 2023). In particular, the rationality of accounting judgments and decisions, adapting the framework of Jarrahi (2018), may be improved by AI in two main ways. First, in scenarios of scarcity, namely characterized by the absence of adequate data, AI-powered systems can intercept and gather useful data for professionals, thus making them take more informed decisions. Second, in scenarios of complexity, thus characterized by the presence of a huge amount of data, AI-powered systems can interpret and transform it into useful information for professionals. Moreover, accounting practices performed through AI applications were found to be more efficient, both in terms of time and costs, than those performed by humans (DAVENPORT, 2018).

Nevertheless, the use of AI-based applications in accounting is not free of limitations. First, AI applications have repeatedly demonstrated that they are not totally free from the same cognitive distortions that afflict the humans who program them. In fact, AI applications are programmed by Machine Learning (ML) algorithms, which effectively teach the machine how to act in different situations. Precisely in this teaching phase, the machine can inherit cognitive distortions from human (ALELYANI, 2021). Further critical issues are related to the very low transparency of the ML algorithms underlying the operation of the machine (KOKINA and DAVENPORT, 2017); the lack of privacy limits with respect to the data that the machine can process (LOBERA et al., 2020); to ethical problems regarding the risk of human work replacement (HUANG and RUST, 2018).

In a such lively research context, animated by the clash between utopian and dystopian future visions regarding the myriad of AI applications also in accounting practices, there is not an historically oriented analysis of the AI evolution within the accounting field. Such contribution would facilitate critical analysis, enabling scholars and practitioners to assess the efficacy, limitations, and future prospects of AI applications for accounting practices. In this view, we want to scientifically trace the evolution of the widest possible range of AI applications within the whole accounting domain. With this aim, we, aligned with other authoritative historical analyses on accounting topics (e.g., BAKER et al., 2023; SCHÄFFER and BINDER, 2008), decided to employ a bibliometric analysis. Indeed, bibliometric analysis serves as a comprehensive tool to uncover the historical narrative, evolution, and impact of whole disciples (DE BATTISTI and SALINI, 2013). By dissecting publication data, it not only illuminates past trends but also provides valuable insights for shaping future research agendas, fostering collaborations, and making informed decisions in the accounting domain (BEHREND and EULERICH, 2019).

In a holistic vision, the results of our historical analysis mark the boundary between old and new AI-based applications for accounting practices, highlight the drivers and critical issues of their use, and highlight the practical implications related to them but still poorly studied. The results of this analysis are thus directed to accounting researchers, practitioners, and policy makers. Indeed, tracking the evolution of concepts and frameworks in AI within accounting literature allows researchers to adapt their focus accordingly. Moreover, such clear historical and conceptual picture helps accounting researchers, practitioners and policy makers to better contextualize the upcoming AI chances, freely from both the dystopia and the utopia of such chances. Finally, practitioners and policymakers are provided with evidence-based insights, helping them make informed decisions related to the integration of AI in accounting practices, education, and regulations.

In order to facilitate the reading and understanding of this article, we report its organization below. In section 2, we explain the methodological design with particular regard to data collection and data analysis techniques. In section 3, we report findings of the bibliometric analysis divided into three main subsections, namely 3.1 contributions over the years, 3.2 trend topics, 3.3 bibliographic coupling. In section 4, we draw conclusions, and describe future research suggestions as well as implications coming from our work.

2. Methodology

The bibliometric analysis has been used by other authoritative accounting contributions to historically investigate how accounting literature integrated due phenomena (e.g., LINNENLUECKE et al., 2020; RATZINGER-SAKEL and TIEDEMANN, 2022). Indeed, bibliometric summaries vast amounts of bibliometric data, especially when the review's purpose is wide and the dataset is too big for manual review, to present the current state of the intellectual structure and new patterns in a research subject or area (DONTHU et al., 2021).In order to perform the best bibliometric analysis possible, among the available software, authors chose *Bibliometrix* (ARIA and CUCCURULLO, 2017) and *VosViewer* (VAN ECK and WALTMAN, 2010).

Although bibliometric analysis is central in our methodological approach, we followed a more complex research design. A more complex approach concerns the main AI literature review, which led to the selection of AI-based applications, then used as keywords to select accounting articles. The research design is fully depicted in Figure 1 and carefully described in steps below.

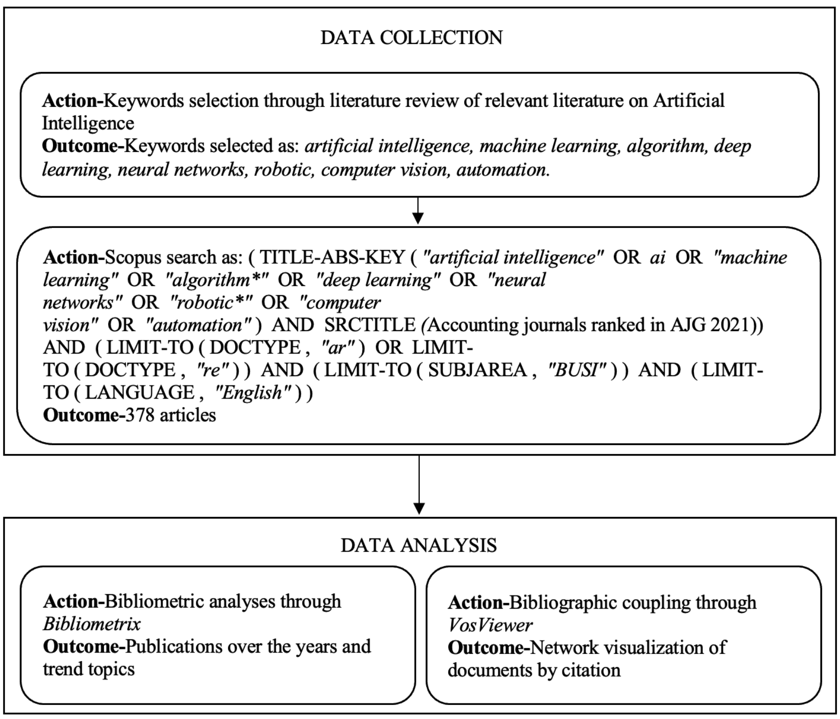

Figure 1. Research design

In particular, our methodological procedure is articulated as follows:

1) We reviewed the relevant literature on AI, with specific regard to its evolution under historical lenses, to extract the keywords (whose definitions are included in Appendix A) which correspond to key AI applications emerged over the years. The review of

the main AI literature was necessary to select keywords that represent specific AI applications (e.g., "neural networks") rather than generic keywords (e.g., "Artificial Intelligence"). Such generic keywords would have led to the selection of articles in fewer numbers and above all unable to describe the evolution of the discipline. In fact, the term "Artificial Intelligence" has recently established in the accounting literature, while the term "neural networks" dates back many years and it is therefore able to help us trace the evolution of the discipline.

2) We entered the keywords in Scopus to search for English articles focused on AI applications, published in relevant accounting journals (i.e., ranked by the Academic Journal Guide 2021). To transparently report, in Appendix B, the protocol used for articles identification, we adopt the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which is a comprehensive guideline crafted by Page et al. (2021). The paper collection relied primarily on Scopus due to its extensive coverage of papers and peer-reviewed journals (YONG-HAK, 2013). Scopus is renowned for its comprehensive English-language research coverage and, unlike Google Scholar, it is less susceptible to biases from data inconsistencies, lack of transparency, and citation count manipulation (MONGEON and PAUL-HUS, 2016). Previous studies have consistently favoured Scopus over other databases, establishing it as the preferred option for literature reviews and bibliometric analyses (MONGEON and PAUL-HUS, 2016), even in the accounting domain (e.g., GROSSI et al., 2020; UMAR et al., 2022).
3) We analysed the final sample of articles collected (378) through two bibliometric software, namely *Bibliometrix* and *VosViewer*. The choice of employing two bibliometric software is instrumental to report the graphs chosen as the best to pursue our research objectives. Therefore, *Bibliometrix* was employed as able to show the years of publications and the trend topics (Figures 2 and 3), while *VosViewer* was employed as able to show the bibliographic coupling of accounting research on AI-based applications in accounting practices (Figure 4). The same methodological approach, based on the combination of these two bibliometric software, has already been adopted in authoritative bibliometric analyses within accounting domain (e.g., VATIS et al., 2023).

3. Bibliometric analysis for understanding past, present and future of accounting research on AI-based applications

The bibliometric analysis conducted provides three types of output (i.e., 3.1 Contributions over the years, 3.2 Trend topics, and 3.3 Bibliographic coupling) which, interpreted together, provide a broad and objective picture of the evolution of accounting research under the pressure of AI-based applications (see Appendix A for definitions of all the AI-based applications cited in this paper).

3.1 Contributions over the years

The graph reported in Figure 2 illustrates the dynamic evolution of research articles focusing on AI within the accounting domain over the years.

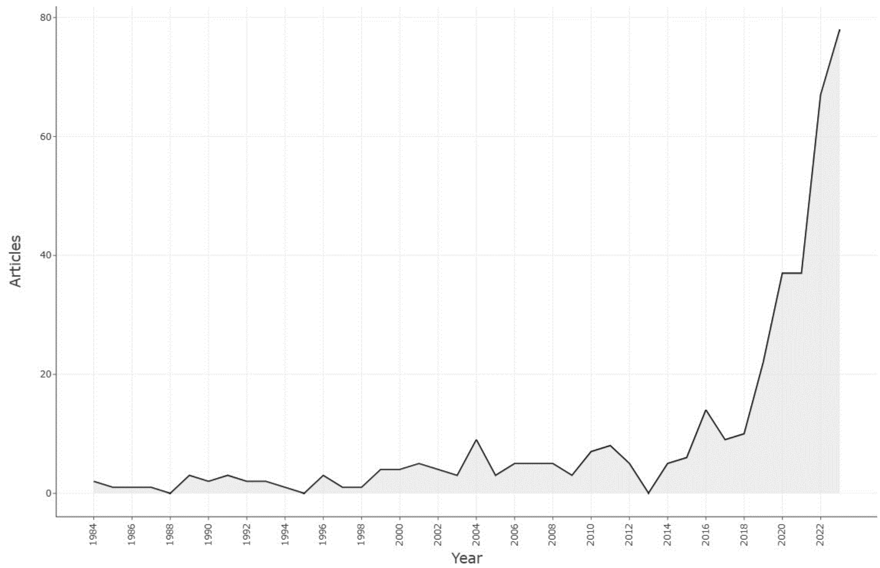

Figure 2. Accounting contributions on AI over the years

After a contentious discussion on the space-time coordinates of AI's origins, the authors come to agree that can be found in 1950. In that year, Turing proposed the "Turing test" in the essay *Computing machines and intelligence.* According to this test, a machine would be qualified as intelligent if a person could not identify that its conduct was different from that of a human. Nevertheless, time of AI was not come yet. Mostly the lack of public funding determined the winter of artificial intelligence, lasted until the 1980s (HAENLEIN and KAPLAN, 2019). From this unsuccessful period, we came out in the 80s thanks to the already widespread use of computers in businesses, industry-specific artificial intelligence systems, i.e., those used for logistics management. In this vein, the first accounting studies on AI (e.g., Merchant, 1984; Shih and Sunder, 1987) coincides with this period, as visible in Figure 2.

From the first studies of the mid-eighties until 2018, the use of AI-technologies has been constant but limited. We essentially attributed this phenomenon to the lack of economically affordable discoveries, whether compared to other revolutionary periods, applicable to business contexts. It is therefore possible to notice a trend that was only slightly increasing over this long period, and then became overwhelming from the end of the 2010s. In fact, since the end of the 2010s, a series of disruptive software-based applications of AI (i.e., data analytics, ML, text mining) have spread, also replacing the existing ones. An explanatory case is that of Deep Learning (DL), which reinvigorated the prominence of Neural Networks when, in 2015, Google's "AlphaGo" program achieved victory over the world champion in the intricate game of "Go". Thus, such innovative AI-applications make professionals and organizations raise their gaze on the more effective and efficient carrying out of several accounting practices (RANTA *et al.*, 2023).

3.2 Trend topics

The graph reported in Figure 3 tracks the topics of articles across years, reflecting the trends on AI-based applications within the accounting domain, thus highlighting obsolete, consolidated, and emerging technologies to carry out accounting practices.

For each authors' keyword listed on the left as "term", there corresponds a dot and a line. The dot's size increases as the number of articles that used that keyword increases, however, the horizontal line demarcates the period between the years of publication of the first and last article that used that keyword.

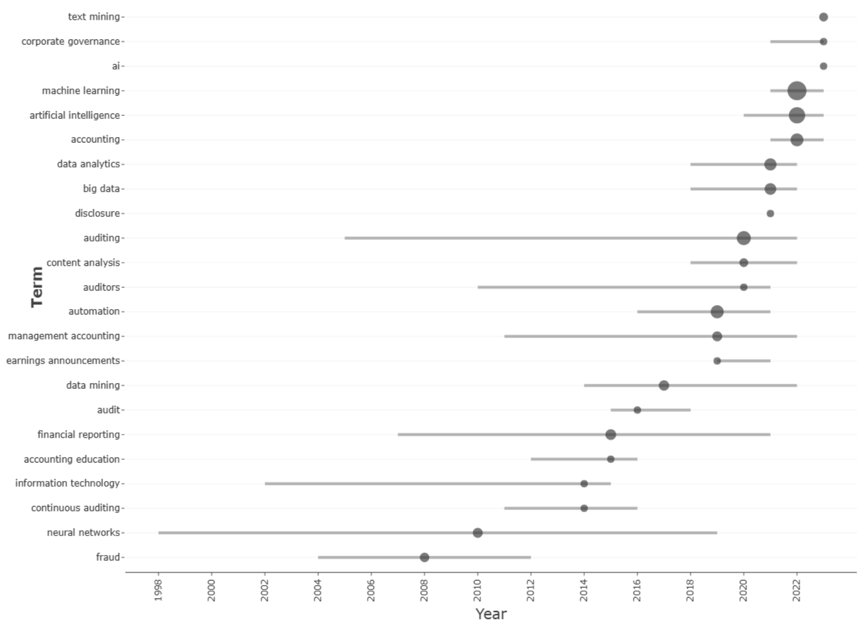

Figure 3. Trend topics

Accounting research on AI, since 1990s, heavily focused on implementing "neural networks" (at the bottom of Figure 3) for fraud detection (refer to "fraud") and critical financial cases in general. Indeed, a tailored approach of Neural Networks for fraud detection was proposed by Busta and Weinberg (1998), who introduced a procedure leveraging artificial Neural Networks to identify potential data manipulation by analyzing digit distributions, yielding promising results in detecting contaminated financial data.

Especially the late 2010s, it is much debated the integration of "automation" within the auditing domain, as this process has encountered unique challenges and differing rates of adoption over time. Huang and Vasarhelyi (2019), despite in a proactive view, observed a delayed embrace of automation in auditing due to the distinctive nature of the field, where tasks demand nuanced professional judgment.

The use of big data analytics (refer to "big data" and "data analytics") has generated significant discussions and transformations within the profession, especially in the really first years of 2020s. Indeed, Kend and Nguyen (2020) shed light on the positive impacts of big data analytics, AI, and robotics in liberating auditors from manual tasks, advocating for regulatory alignment amid rapid technological advancements. Additionally, Agostini et al. (2022) delve into the intersection of big data analytics, non-financial disclosure, and corporate accountability, spotlighting the intricate relationship between data analytics and social accountability.

ML (refer to "machine learning") is truly taking the scene in different fields of recent accounting research. For instance, Neuman and Sheu (2022) bring attention to the potential of ML in enhancing IRS (Internal Revenue Service) efficiency for tax compliance while addressing privacy and fairness concerns, linking audit procedures, fairness perceptions, and compliance behaviors. Moreover, Nielsen (2022) urgently calls management accountants to engage with ML concepts to align their skills with evolving demands, highlighting a gap in the adoption of these technologies within the field.

Finally, the last dot in temporal order signals interest in text mining (refer to "text mining"). Thanks to text mining technique, the unstructured textual data, as emerge from the narrative sections of the financial disclosures, are extracted and interpreted to facilitate their use by the stakeholders to whom such data is addressed. We interpret this growing interest in the topic also as a consequence of the increase in corporate financial information presented in a narrative way (HASAN et al., 2020).

3.3 Bibliographic coupling

In this section, we analyze the topics of the accounting literature regarding the AI applications that have occurred over the years. With these aims, we choose to employ a bibliographic coupling of documents by citation, offering its network visualization (Figure 4). Bibliographic coupling refers to the relationship between documents based on their shared references or citations. The size of the dots depends on the number of connections that a particular document has with other documents within a network of related works. Links represent connections between different documents that cite similar or the same sources, suggesting a thematic or conceptual connection between them (van Eck & Waltman, 2017). Bibliographic coupling has already been employed by relevant accounting research to explain, connect, and reveal research topics (e.g., BAKER et al., 2023; CEPÊDA et al. 2022).

The bibliographic coupling is shown through a network visualization (Figure 4), that gives a thematic perspective on articles' content. In practice, the bigger dots represent the articles sharing most citations with others (e.g., "li f. (2010)"), while the smaller dots represent the articlessharing least citations with others (e.g., "krieger f. (2021)"). The link and proximity between two dots are strong whether the number common citations is high (e.g., "henrye. (2016)" and "el-hajm. (2019)"), weak whether the number of common citations is low (e.g., "Leitner-hanetseders. (2021)" and "van heldenj. (2019)"). The same color is attributed to dots sharing citations thus coherent in topics treated (i.e., "jones s. (2017)" and "Charitou a. (2004)").

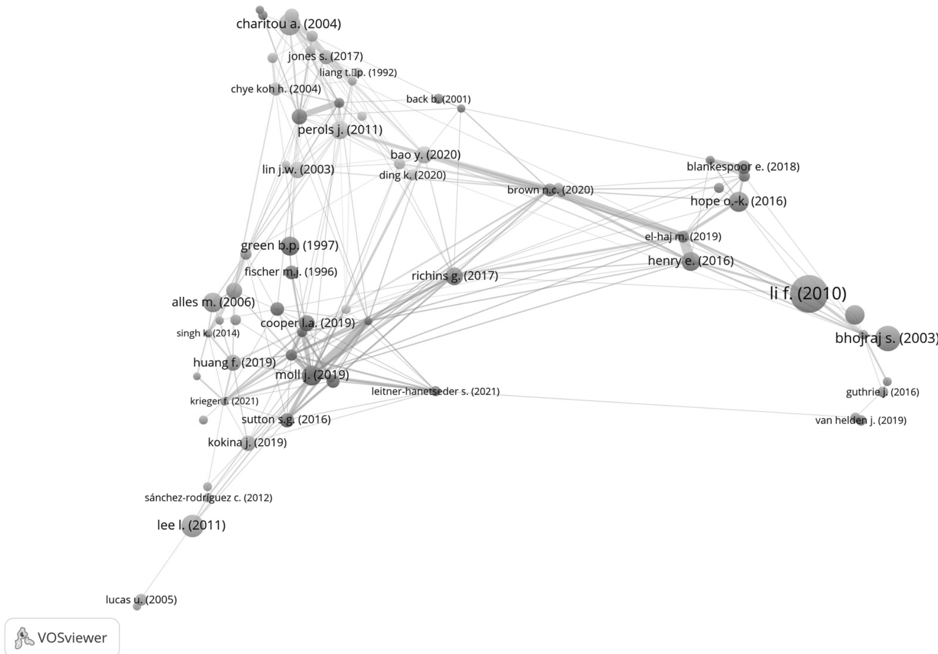

Figure 4. Network visualisation of bibliographic coupling

Cluster 1 (red): critical perspectives on the transition of accounting professions

In the late 1990s and early 2000s, there was an emphasis on the development of new technologies aimed at enhancing efficiency and effectiveness of accounting and audit professions. However, findings from Fischer (1996) shed light on the misalignment between the anticipated benefits of these technologies and their actual impact. Efficiency gains were not directly attributed to technology adoption but rather stemmed from the reconfiguration or elimination of existing audit procedures. This highlighted the importance of understanding how technology interacts with audit processes and the proactive role auditors play in leveraging these tools effectively. In this vein, but more recently, new technological advancements such as Robotic Process Automation (RPA), discussed by Cooper et al. (2019), have introduced efficiency gains but also raised concerns about potential fee reductions due to decreased hours worked. Interestingly, RPA adoption in accounting, unlike other domains, has been primarily driven by lower-level employees, indicating a bottom-up approach to technological integration. Again, studies like those by Kend and Nguyen (2020), beyond opportunities, showcase the contemporary challenges. The COVID-19 pandemic has posed unprecedented challenges for accountants and auditors, impacting quality of their work through various channels such as remote work and assessment procedures. Recommendations to face such challenges include investments in digital programs for accountants to adapt their skillsets and remain relevant, and the temporary relaxations in compliance requirements to adapt to the remote working environment. Finally, about challenges, a consolidated presence of both empirical and conceptual studies exploring the ethical implications of AI-based applications in accounting practices was expected. Such expectation, unfortunately, did not align with the literature reviewed, because ethical challenges were touched in a very few and recent works (e.g., LEHNER et al., 2022; LEITNER-HANETSEDER et al., 2021).

Cluster 2 (blue): technologies for financial narrative analysis

This cluster gathers studies which, mostly published in recent years, shed light on AI-based applications for financial narrative analysis and its implications. Henry and Leone (2016) emphasize the efficacy of domain-specific wordlists in word-frequency tone measures, demonstrating superior predictability of market reactions to earnings announcements and greater statistical power in short-window event studies. Wei et al. (2019) introduce a novel semi-supervised text mining approach, the naive collision algorithm, to comprehensively identify 21 bank risk factors from qualitative textual risk disclosures in financial statements. Outperforming traditional unsupervised methods, their approach provides a detailed analysis of the changing importance of each risk factor over time. Brown et al. (2019) employ a ML technique to assess the thematic content's incremental informativeness in predicting intentional misreporting. Their Bayesian topic modeling algorithm identifies semantically meaningful topics that significantly improve misreporting detection much more when integrated with traditional variables.

Cluster 3 (violet): AI reshaping financial reporting and financial reporting strategies

AI has demonstrated to be able to play a pivotal role in reshaping financial reporting across various dimensions. Studies within this cluster collectively underscore AI's multifaceted impact on financial reporting, from predictive analytics to strategic stakeholder-centric disclosures, emphasizing its transformative potential. About early solutions, Debreceny and Gray (2001) discuss challenges in utilizing the web for financial reporting and propose eXtensible Markup Languageand eXtensible Business Reporting Language, indicating AI's potential to improve information retrieval and consistency in financial data across diverse sources. Additionally, van Helden and Reichard (2019) stress AI's role in understanding different user groups' information needs, emphasizing the importance of tailoring financial reporting to specific stakeholders. In the same line, Corazza et al. (2020) examine sustainability disclosures post-disaster, revealing how AI-driven textual and visual signals shape corporate image restoration strategies.

Cluster 4 (green): AI to improve audit profession

This cluster studies portray AI's transformative impact on auditing, from enhancing efficiency and accuracy through automation to leveraging data mining for fraud detection and RPA for routine tasks, thus reshaping the whole audit profession. First observations were focused on the automation of the profession. Indeed, Manson et al. (2001) explore the sociotechnical aspects of audit automation, highlighting its value as a symbol of market competitiveness and its role in reshaping organizational structures. Few years later, over audit credibility post-scandals, Alles et al. (2004) advocate for continuous assurance augmented with a "black box log file" for auditors' actions, reinforcing transparency and credibility. Still, Alles et al. (2006) illustrate how the continuous monitoring of business process controls, taking into exam the Siemens Corporation, necessitated a reengineering of audit processes, emphasizing the critical role of managing audit alarms. Once the time of data mining came for audit, Jans et al. (2010) discuss data mining strategies in fraud detection and prevention, underscoring their applicability in assessing internal fraud risk, while Werner (2017) delves into process mining as an innovative technique for audit support. More recently, audit met RPA, thus Huang and Vasarhelyi (2019) thought RPA for auditing by demonstrating its ability to automate routine tasks, enabling auditors to focus on higher judgment tasks.

Cluster 5 (turquoise): models for predictive financial analyses

The studies of this cluster, which slowed few years ago, witness the significant advancements of the predictive models for financial analysis, mostly shifting from traditional Neural Networks to "new age" classifiers. Initially, Liang et al. (1992) explored LIFO/FIFO classification models, finding Neural Networks as the best in terms of predictive accuracy in hold-out tests. Thus, basing on Neural Networks, Koh and Tan (1999) investigated and valued a novel approach for assessing a firm's going concern status. Again, Neural Networks, alongside logit methodology, yielded reliable financial distress predictions for UK public industrial firms one year prior to failure (CHARITOU et al., 2004). Anyway, in those years, some criticisms and, at the same time, adjustments to the traditional Neural Network models also arrived. In this sense, Neves and Vieira (2006) demonstrated how their Neural Network-learning algorithm outperformed traditional Neural Networks, providing a useful measure of credit risk. Much more recently, Jones et al. (2017) investigated the predictive performance of various classifiers for corporate bankruptcy prediction. While simple classifiers like logit and linear discriminant analysis performed reasonably well, "new age" classifiers such as support vector machines and random forests exhibited superior predictive capabilities and practical appeal.

Cluster 6 (yellow): AI for fraud prediction and detection

The articles of this cluster trace the evolution of fraud prediction and detection under the effects of AI-based innovations. Initially, Friedlob and Schleifer (1999) introduced fuzzy logic as a method to handle different types of uncertainty, potentially aiding auditors in managing audit risk more effectively. Then, Lin et al. (2003) delved into the efficacy of fuzzy Neural Networks and fuzzy logic-based Expert Systems in fraud detection within financial settings, demonstrating their superiority over traditional statistical models and Neural Networks. When the time of ML came, many years later, Perols (2011) highlighted diversity in the performance of AI models, hence indicating that some ML methods excel in fraud detection, others like logistic regression and support vector machines perform well in certain contexts. Coherently, Bertomeu et al. (2021) emphasized the role of ML in detecting ongoing accounting misstatements by analyzing vast datasets from various sources, highlighting the importance of interactions between accounting, audit, and market variables.

Cluster 7 (orange): technological advancements for efficient accounting routines

These studies underscore the efficiency process of various accounting routines under the effects of technological advancements. For instance, Sánchez-Rodríguez and Spraakman (2012) focus on refining theories regarding the impact of Enterprise Resource Planning on management accounting. Their research highlights how Enterprise Resource

Planning implementations enhance computing power, standardize transaction processing, and extend charts of accounts, resulting in more accurate, timely, and consistent information. Standardization and automation reduce data entry tasks for management accountants, allowing for greater analytical focus. More recently, Kokina and Blanchette (2019) delved into RPA, underlining its impact on accounting and finance tasks. They stressed the need for organizations to not only secure technical capability but also standardize and optimize processes, redefining internal controls and engaging in selective automation of structured, repeated, rules-based tasks. Their study showed benefits beyond cost savings, thus including lower error rates and enhanced report quality.

Cluster 8 (brown): Neural Networks as early AI models for accounting

This cluster gather studies, early developed, delineated the integration of Neural Networks as initial models into AI technologies for accounting practices. Despite Neural Networks are now being overcome, they signed the first convincing shifts towards sophisticated analysis methodologies in accounting and auditing domains. Back et al. (2001) emphasized the evolving role of technology in accounting information analysis, specifically highlighting the shift from solely analyzing numerical data to incorporating qualitative information extracted from annual reports. Their findings revealed distinct differences in clustering results between the two types of information, indicating the potential for Neural Networks, to unravel new insights previously untapped in qualitative data analysis within accounting. Instead, Calderon and Cheh (2002) concentrated on the application of Neural Networks in auditing, particularly in risk assessment. They explored and valued the capacity of Neural Networks to process diverse evidence simultaneously, aiding auditors in risk evaluation and judgment.

4. Conclusions

The evolutionary journey of accounting research on AI reveals a timeline marked by watershed moments and transformative applications for accounting practices. Rooted in landmark proposition of Turing (1950), AI's progression was hindered by funding constraints until the 1980s, when business-specific AI systems began emerging. From the mid-80s until the late 2010s, AI's growth in accounting was steady but limited by affordable applicability, indeed the few researches timidly introduced basic technologies while questioning about their effectiveness and efficiency compared to traditional methods (Fischer, 1996). However, the late 2010s witnessed a seismic shift with disruptive AI applications like deep DL and ML reshaping accounting practices (Nielsen, 2022).

Such evolutionary journey through AI-based applications in accounting, carefully outlined in section 3 and just recalled in these last lines, allowed us to identify gaps and research trends thus substantiating our suggestions for future accounting research. In particular, future accounting researchers are encouraged to: (i) explore the evolving landscape of AI in accounting beyond Neural Networks, emphasizing disruptive technologies like ML, DL, and RPA to optimize especially auditing processes and financial reporting analysis; (ii) deepen the opportunities and implications of text mining for analysis of narrative financial disclosures, with particular regard to the transparency and decision-making quality on the side of financial disclosures' readers; (iii) conduct longitudinal studies tracking the trajectory of AI integration in accounting practices, singularly considered, to assess its ongoing impact, challenges, and opportunities in a dynamic technological landscape; (iv) delve into the ethical implications associated with the integration of AI-based applications in accounting practices, hopefully through the five dimensions of objectivity, privacy, transparency, accountability, trustworthiness (Lehner et al., 2022).

Furthermore, our analysis can serve as a valuable resource for accounting professionals, as we offered insights into the latest trends, best practices, challenges, and ethical considerations associated with the integration of AI-based applications in the accounting field. In particular, accounting professionals are suggested to: (i) encourage collaborations between AI specialists, accountants, and auditors to bridge the gap between technological advancements and effective implementation in accounting practices; (ii) embrace continuous learning, adapting skillsets to align especially with advanced analytics, ML, DL, and RPA tools; (iii) integrate the use of AI-based applications within corporate performance management systems, in order to monitor their efficiency, effectiveness, and risks in the corporate implementations.

Finally, even policy makers may exploit our analysis as it provides insights into the current landscape, potential future developments, and considerations for creating a regulatory environment that encourages responsible and beneficial AI adoption in the accounting sector. In this sense, policy makers are invited to: (i) support initiatives aimed at enhancing education and training for accounting professionals to equip them with the necessary skills to harness AI's potential effectively; (ii) address ethical considerations surrounding AI implementation in accounting, emphasizing transparency, accountability, and fairness in algorithmic decision-making.

Nevertheless, our work is not free from limitations. First, our analysis is based on articles published on accounting journals ranked by the Academic Journal Guide 2021. Although the choice is motivated by the desire to guarantee a high standard of contributions analyzed, this does not imply that journals outside the aforementioned ranking cannot equally report valuable contributions. Second, our bibliometric analysis, as confined to publications on accounting journals, hardly integrates external influences (e.g., managerial organizational forces, socio-cultural issues). Such external influences would contribute to convincingly explain the adoption of AI-based applications for carrying out accounting practices.

RICCARDO CAMILLI
Ricercatore di Economia Aziendale

Università degli Studi di Roma Tor Vergata
Dipartimento di Management e Diritto

ALESSANDRO MECHELLI
Professore Ordinario di Economia Aziendale

Università degli Studi di Roma Tor Vergata
Dipartimento di Management e Diritto

IVO HRISTOV
Professore Associato di Economia Aziendale

Università degli Studi dell'Aquila
Dipartimento di Ingegneria Industriale e
dell'Informazione e di Economia

References

AGOSTINI M., ARKHIPOVA D., MIO C. (2022), "Corporate accountability and big data analytics: is non-financial disclosure a missing link?" in *Sustainability Accounting, Management and Policy Journal*, n. 7, pagg. 62-89.

ALELYANI S. (2021), "Detection and Evaluation of Machine Learning Bias", in *Applied Sciences*, n. 14.

ALLES M., BRENNAN G., KOGAN A., VASARHELYI M. A. (2006), "Continuous monitoring of business process controls: A pilot implementation of a continuous auditing system at Siemens", in *International Journal of Accounting Information Systems*, n. 2, pagg. 137-161.

ALLES M.G., KOGAN A., VASARHELYI M.A. (2004), "Restoring auditor credibility: Tertiary monitoring and logging of continuous assurance systems", in *International Journal of Accounting Information Systems*, n. 2, pagg. 183-202.

ARIA M., CUCCURULLU C. (2017), "Bibliometrix: An R-tool for comprehensive science mapping analysis", in *Journal of Informetrics*, n. 4, pagg. 959-975.

BACK B., TOIVONEN J., VANHARANTA H., VISA A. (2001), "Comparing numerical data and text information from annual reports using self-organizing maps", in *International Journal of Accounting Information Systems*, n. 4, pagg. 249-269.

BAKER H. K., KUMAR S., PANDEY N., KRAUS S. (2023), "Contemporary Accounting Research: A retrospective between 1984 and 2021 using bibliometric analysis", in *Contemporary Accounting Research*, n. 1, pagg. 196-230.

BEHREND J., EULERICH M. (2019), "The evolution of internal audit research: a bibliometric analysis of published documents (1926–2016)", in *Accounting History Review*, n. 1, pagg. 103-139.

BERTOMEU J., CHEYNEL E., FLOYD E., PAN, W. (2021), "Using machine learning to detect misstatements", in *Review of Accounting Studies*, n. 2, pagg. 468-519.

BROWN N.C., CROWLEY R.M., ELLIOT W.B. (2019), "What Are You Saying? Using topic to Detect Financial Misreporting", in *Journal of Accounting Research*, n. 1, pagg. 237-291.

BUSTA B., WEINBERG R. (1998), "Using Benford's law and neural networks as a review procedure", in *Managerial Auditing Journal*, n. 6, pagg. 356-366.

CALDERON T.G., CHEH J. J. (2002), "A roadmap for future neural networks research in auditing and risk assessment", in *International Journal of Accounting Information Systems*, no. 4, pagg. 203-236.

CEPEDA C., MONTIERO A. P., SILVA R., FERREIRA-DA-SILVA A. (2022), "Accounting history: a bibliometric literature review", in *Revista de Contabilidade e Controladoria*, n. 2.

CHARITOU A., NEOPHYTOU E., CHARALAMBOUS C. (2004), "Predicting corporate failure: empirical evidence for the UK", in *European Accounting Review*, n. 3, pagg. 465-497.

CHEN M., ZHANG Q. (2014), "Data-intensive applications, challenges, techniques and technologies: A survey on Big Data", in *Information Sciences*, pagg. 314-347.

COOPER L. A., HOLDERNESS JR D. K., SORENSEN T. L., WOOD D. A. (2019), "Robotic process automation in public accounting", in *Accounting Horizons*, n. 4, pagg. 15-35.

CORAZZA L., TRUANT E., SCAGNELLI S. D., MIO C. (2020), "Sustainability reporting after the Costa Concordia disaster: a multi-theory study on legitimacy, impression management and image restoration", in *Accounting, Auditing & Accountability Journal*, n. 8, pagg. 1909-1941.

CORMEN T. H., LEISERSON C. E., RIVERST R. L., STEIN C. (2009), *Introduction to Algorithms*, MIT Press.

DAVENPORT T. H. (2018), *The AI advantage: How to put the artificial intelligence revolution to work*, MIT Press.

DE BATTISTI F., SALINI S. (2013), "Robust analysis of bibliometric data", in *Statistical Methods & Applications*, n. 2, pagg. 269-283.

DEBRECENY R., GRAY G.L. (2001), "The production and use of semantically rich accounting reports on the Internet: XML and XBRL", in *International Journal of Accounting Information Systems*, n. 1, pagg. 47-74.

DONTHU N., KUMAR S., MUKHERJEE D., PANDEY N., LIM W. M. (2021), "How to conduct a bibliometric analysis: An overview and guidelines", in *Journal of Business Research*, pagg. 285-296.

FELDMAN R., SANGER J. (2007), *The Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data*, Cambridge University Press.

FISCHER M.J. (1996) "'Real-izing" the benefits of new technologies as a source of audit evidence: An interpretive field study", in *Accounting, Organizations and Society*, n. 2-3, pagg. 219-242.

FRIEDLOB G.T., SCHLEIFER L.L.F. (1999), "Fuzzy logic: Application for audit risk and uncertainty", in *Managerial Auditing Journal*, n. 3, pagg. 127-137.

GOODFELLOW I., BENGIO Y., COURVILLE A. (2016), *Deep Learning*, MIT Press.

GROSSI G., KALLIO K. M., SARGIACOMO M., SKOOK M. (2020), "Accounting, performance management systems and accountability changes in knowledge-intensive public organizations: a literature review and research agenda", in *Accounting, Auditing & Accountability Journal*, n. 1, pagg. 256-280.

HAENLEIN M., KAPLAN A. (2019), "A brief history of artificial intelligence: On the past, present, and future of artificial intelligence", in *California Management Review*, n. 4, pagg. 5-14.

HAN, J., KAMBER, M., PEI, J. (2011), *Data Mining: Concepts and Techniques*, Morgan Kaufmann.

HASAN M. M. (2020), "Readability of narrative disclosures in 10-K reports: does managerial ability matter?", in *European Accounting Review*, n. 1, pagg. 147-168.

HENRY E., LEONE J.A. (2016), "Measuring qualitative information in capital markets research: Comparison of alternative methodologies to measure disclosure tone", in *The Accounting Review*, n. 1, pagg. 153-178.

HUANG F., VASARHELYI M.A. (2019), "Applying robotic process automation (RPA) in auditing: A framework", in *International Journal of Accounting Information Systems*.

HUANG M. H., Rust R. T. (2018), "Artificial intelligence in service", in *Journal of Service Research*, n. 2, pagg. 155-172.

JÄMSÄ-JOUNELA S. L. (2007), "Future trends in process automation", in *Annual Reviews in Control*, n. 2, pagg. 211-220.

JANS M., LYBAERT N., VANHOOF K. (2010), "Internal fraud risk reduction: Results of a data mining case study", in *International Journal of Accounting Information Systems*, n. 1, pagg. 17-41.

JARRAHI M. H. (2018), "Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making", in *Business Horizons*, n. 4, pagg. 577-586.

JONES S., JOHNSTONE D., WILSON R. (2017), "Predicting Corporate Bankruptcy: An Evaluation of Alternative Statistical Frameworks", in *Journal of Business Finance and Accounting*, n. 1-2, pp. 3-34.

KASTNER J. K., HONG S. J. (1984), "A review of expert systems", in *European Journal of Operational Research*, n. 3, pagg. 285-292.

KEND M., NGUYEN L.A. (2020), "Big Data Analytics and Other Emerging Technologies: The Impact on the Australian Audit and Assurance Profession"', in *Australian Accounting Review*, n. 4, pagg. 269-282.

KOH H.C., TAN S.S. (1999), "A neural network approach to the prediction of going concern status", in *Accounting and Business Research*, n. 3, pagg. 211-216.

KOKINA J., BLANCHETTE S. (2019), "Early evidence of digital labor in accounting: Innovation with Robotic Process Automation", in *International Journal of Accounting Information Systems*.

KOKINA J., DAVENPORT T. H. (2017), "The emergence of artificial intelligence: How automation is changing auditing", in *Journal of Emerging Technologies in Accounting*, n. 1, pagg. 115-122.

LEHNER O. M., ITTONEN K., SILVOLA H., STRÖM E., WÜHRLEITNER A. (2022), "Artificial intelligence based decision-making in accounting and auditing: ethical challenges and normative thinking", in *Accounting, Auditing & Accountability Journal*, n. 9, pagg. 109-135.

LEITNER-HANETSEDER S., LEHNER O. M., EISL C., FORSTENLECHNER C. (2021), "A profession in transition: Actors, tasks and roles in AI-based accounting", in *Journal of Applied Accounting Research*, n. 3, pagg. 539-556.

LIANG T. P., CHANDLER J. S., HAN I., ROAN J. (1992), "An empirical investigation of some data effects on the classification accuracy of probit, ID3, and neural networks", in *Contemporary Accounting Research*, n. 1, pagg. 306-328.

LIN J.W., HWANG M.I., BECKER J.D. (2003), "A fuzzy neural network for assessing the risk of fraudulent financial reporting", in *Managerial Auditing Journal*, n. 8, pagg. 657-665.

LINNENLUECKE M. K., MARRONE M., SINGH A. K. (2020), "Sixty years of Accounting & Finance: a bibliometric analysis of major research themes and contributions", in *Accounting & Finance*, n. 4, pagg. 3217-3251.

LOBERA J., FERNÁNDEZ RODRÍGUEZ C. J., TORRES-ALBERO C. (2020), "Privacy, values and machines: Predicting opposition to artificial intelligence", in *Communication Studies*, n. 3, pagg. 448-465.

MANSON S., MCCARTNEY S., SHERER M. (2001), "Audit automation as control within audit firms", in *Accounting, Auditing & Accountability Journal*, n. 1, pagg. 109-130.

MARCELLO R., CAFARO E. (2020), "Gli indici di allerta: dalla diagnosi all'emersione della crisi", in *Rivista Italiana di Ragioneria e di Economia Aziendale*.

MITCHELL T. (1997), *Machine Learning*, McGraw Hill.

MONGEON P., PAUL-HUS A. (2016), "The journal coverage of Web of Science and Scopus: a comparative analysis", in *Scientometrics*, n. 1, pagg. 213-228.

NEUMAN E.L., SHEU R.J. (2022), "Big Data Analytics in IRS Audit Procedures and Its Effects on Tax Compliance: A Moderated Mediation Analysis", in *Journal of the American Taxation Association*, n. 2, pagg. 97-113.

NEVES J.C., VIERA A., (2006), "Improving bankruptcy prediction with Hidden Layer Learning Vector Quantization", in *European Accounting Review*, n. 2, pagg. 253-271.

NIELSEN S. (2022), "Management accounting and the concepts of exploratory data analysis and unsupervised machine learning: a literature study and future directions", in *Journal of Accounting and Organizational Change*, n. 5, pagg. 811-853.

NØRREKLIT H., NØRREKLIT L., MITCHELL F. (2010), "Towards a paradigmatic foundation for accounting practice", in *Accounting, Auditing & Accountability Journal*, n. 6, pagg. 733-758.

PAGE M. J., MCKENZIE J. E., BOSSUYT P. M., BOUTRON I., HOFFMANN T. C., MULROW C. D., ... MOHER D. (2021), "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews", in *Systematic Reviews*, n. 1, pagg. 1-11.

PEROLS J. (2011), "Financial statement fraud detection: An analysis of statistical and machine learning algorithms", in *Auditing: A Journal of Practice & Theory*, n. 2, pagg. 19-50.

RANTA M., YLINEN M., JÄRVENPÄÄ, M. (2023), "Machine Learning in Management Accounting Research: Literature Review and Pathways for the Future", in *European Accounting Review*, n. 3, pagg. 607-636.

RATZINGER-SAKEL N. V., TIEDEMANN T. (2022), "Fraud in accounting and audit research (1926–2019) - a bibliometric analysis", in *Accounting History Review*, n. 2-3, pagg. 1-47.

RIBEIRO J., LIMA R., ECKHARDT T., PAIVA, S. (2021), "Robotic process automation and artificial intelligence in industry 4.0 - a literature review", in *Procedia Computer Science*, pagg. 51-58.

SÁNCHEZ-RODRÍGUEZ C., SPRAAKMAN G. (2012), "ERP systems and management accounting: A multiple case study", in *Qualitative Research in Accounting and Management*, n. 4, pagg. 398-414.

SCHÄFFER U., BINDER C. (2008), ""Controlling" as an academic discipline: the development of management accounting and management control research in German-speaking countries between 1970 and 2003", in *Accounting History*, n. 1, pagg. 33-74.

SIMON H.A. (1947), *Administrative Behavior*, Free Press, New York City, New York, USA.

SUTTON S. G., HOLT M., ARNOLD V. (2016), ""The reports of my death are greatly exaggerated" – Artificial intelligence research in accounting", in *International Journal of Accounting Information Systems*, pagg. 60-73.

SZELISKI, R. (2010), *Computer Vision: Algorithms and Applications*, Springer.

TURING, A. (1950), "Computing Machinery and Intelligence", in *Mind*, n. 236, pagg. 433-460.

UMAR I. M., MUSTAFA H., LAU W. Y., SIDEK S. (2022), "Ninety-three years of agricultural accounting studies in Scopus journals: a bibliometric analysis from 1923 to 2020", in *Journal of Accounting in Emerging Economies*, n. 5, pagg. 741-760.

VAN ECK N.J., WALTMAN L. (2010), "Software survey: VOSviewer, a computer program for bibliometric mapping", in *Scientometrics*, n. 2, pagg. 523-538.

VAN HELDEN J., REICHARD C. (2019), "Making sense of the users of public sector accounting information and their needs", in *Journal of Public Budgeting, Accounting and Financial Management*, n. 4, pp. 478-495.

VATIS S. E., NERANTZIDIS M., DROGALAS G., CHYTIS E. (2023), "Connecting IFRS and earnings management: a bibliometric analysis", in *Journal of Accounting Literature*.

WANG H., FU T., DU Y., GAO W., HUANG K., LIU Z., ... ZITNIK M. (2023), "Scientific discovery in the age of artificial intelligence", in *Nature*, n. 7972, pagg. 47-60.

WEI L., LI G., ZHU X., LI J. (2019), "Discovering bank risk factors from financial statements based on a new semi-supervised text mining algorithm", in *Accounting & Finance*, n. 3, pagg. 1519-1552.

WERNER M. (2017), "Financial process mining - Accounting data structure dependent control flow inference", in *International Journal of Accounting Information Systems*, pagg. 57-80.

WINSTON P. H. (1992), *Artificial Intelligence*, Addison-Wesley Longman Publishing Co., Inc.

YONG-HAK JO. (2013), *Web of Science*, Thomson Reuters, Toronto.

Appendix A. Definitions of Artificial Intelligence application smentioned in the paper

Name	**Definition**
Algorithm	Adefined sequence of instructions, designed to perform specific computations or operations (Cormen et al., 2009).
Artificial Intelligence (AI)	A discipline focused on creating systems that can perform tasks by simulating human intelligence. It exploits a wide range of algorithms and techniques to enable machines to simulate human cognitive abilities, such as language understanding, learning, problem-solving (Winston, 1992).
Automation	The use of technology, machinery, and systems to automate tasks, thus requiring minimal human intervention (Jämsä-Jounela, 2007).
Big data	The massive volume data, that traditional data processing methods struggle to handle efficiently (Chen and Zhang, 2014).
Computer vision	A subfield of Artificial Intelligence focused on enabling machines, mostly through algorithms, to understand and interpret information under visual forms, such as images or videos (Szeliski, 2010).
Expert System (ES)	An Artificial Intelligence-based program imitatings pecialists' expertise, through rules, logic, and knowledge bases, to interpret data and generate recommendations in specific fields (Kastner and Hong, 1984).
Data mining	The process of discovering patterns, correlations, and insights from large datasets using various techniques from machine learning, statistics, and database systems (Han et al., 2011).
Deep Learning (DL)	A subfield of Machine Learning, inspired by the structures of the human brain, known as artificial Neural Networks, which are designed to recognize patterns and make decisions simulating human reasoning. The term "deep" refers to the multiple layers, and each layer of neurons processes information and passes it on to the next layer, thus allowing the network to progressively extract higher-level features from the input data (Goodfellow et al., 2016).
Machine Learning (ML)	A branch of Artificial Intelligence that focuses on enabling machines to learn and improve from experience without being explicitly programmed. This is grounded on algorithms and statistical models that allow machines to automatically learn and make predictions or decisions basing on data (Mitchell, 1997).
Neural Networks (NNs)	A computational approach inspired by the structure and function of the human brain. These are made up of interconnected nodes, called neurons, and organized in layers. Information flows through the network, where each neuron processes and transmits signals to neurons in the next layer, allowing the network to learn patterns and relationships within data (Goodfellow et al., 2016).
Robotic Process Automation (RPA)	The use of software robots or "bots" to automate humans' tasks, typically the most repetitive and rule-based ones. These bots mimic human actions, within digital systems, to execute tasks such as data entry, file manipulation, and communication across multiple platforms (Ribeiro et al., 2021).
Text mining	The process of extracting information and insights from unstructured textual data. It involves using various techniques from Natural Language Processing, Machine Learning, and computational linguistics (Feldman and Sanger, 2007).

Appendix B. PRISMA framework to report the literature review protocol