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Artificial Intelligence Systems in Accounting and Auditing: A Bibliometric and Exploratory Analysis

Ioana Florina Coita
University of Economics in Bratislava, Faculty of Economics, Department of Finance, Slovakia; University of Oradea, Faculty of Economics, Department of Finance and Accounting, Oradea, Romania; University of Sofia, St. Kliment Ohridski, Department of Finance, Sofia, Bulgaria.
coita.iflorina@gmail.com,
https://orcid.org/0000-0002-0782-2790

Laura Filip
University of Oradea, Faculty of Economics, Department of Finance and Accounting, Oradea, Romania.
laura.filip88@gmail.com,
https://orcid.org/0009-0009-2052-2563

Marius Vlad Pop
University of Oradea, Faculty of Economics, Department of Finance and Accounting, Oradea, Romania.
mariusvpop@gmail.com,
https://orcid.org/0000-0001-5084-9633

Abstract: *This study examines the role of artificial intelligence (AI) in accounting and auditing through a two-stage design that combines bibliometric analysis with an exploratory comparative evaluation of AI-based solutions. The current literature shows a fragmentation between conceptual reviews and vendor-driven case descriptions, while a structured cross-cutting view of how AI technologies are actually integrated into financial workflows, and of how this integration differs by entity size and by the trustworthiness profile of the underlying systems, is still limited. The bibliometric component examines 729 peer-reviewed articles indexed in the Web of Science database (post-2015), processed using VOSviewer for keyword co-occurrence analysis. The exploratory component evaluates ten AI-based solutions against a framework that covers AI subset, functional category, target entity size, audit relevance, and disclosed architectural transparency. The bibliometric results indicate that the field is organised around six dominant terms (artificial intelligence, deep learning, machine learning, performance, classification, and model), reflecting a strong methodological convergence on supervised and deep-learning approaches. The exploratory results show that current AI offerings cluster into three functional categories (process automation, analytics and business intelligence, and predictive or audit-oriented systems), with adoption patterns that differ by company size: small and medium-sized entities (SMEs) gain the most benefits from process automation and optical character recognition, while large entities derive higher value from full-population analytics and ensemble-based anomaly detection. The study contributes a replicable methodological pipeline that links bibliometric mapping with applied tool evaluation, a comparative framework that addresses the often undisclosed AI architecture behind vendor black-box tools, and a discussion of trustworthiness limits, including the constitutive (non-error) nature of probabilistic AI failures, with implications for audit assurance and emerging regulatory frameworks such as the EU AI Act and ISO/IEC 42001.*

Keywords: *artificial intelligence; bibliometric analysis; exploratory analysis; financial data processing; digital transformation; trustworthiness; SME adoption; human–AI interaction.*

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1. Introduction

The selected topic is of great importance and relevance in the context of the increasing impact of artificial intelligence across various industries, including accounting and auditing. It is essential for professionals in these fields to understand the implications of AI technologies in their work, considering the potential benefits associated with the automation of accounting and audit processes, the enhanced speed and accuracy of financial data analysis, and the improvement in the quality of financial information.

At the same time, attention must be given to the risks related to data security and confidentiality, as well as to the potential consequences for employment within the field. The study of this topic enables a deeper understanding of the impact of artificial intelligence in accounting and auditing and contributes to the adaptation and optimisation of practices and policies within this continuously evolving domain.

The chosen topic demonstrates relevance across several dimensions. First, it aims to identify and evaluate the risks associated with the use of AI in accounting and auditing, including issues related to data security, confidentiality,and employment-related implications. The research also contributes to strengthening knowledge and expertise in accounting and auditing by exploring the new paradigms and opportunities generated by artificial intelligence. Another important aspect involves promoting dialogue and collaboration among the academic community, accounting and auditing professionals, and regulatory bodies, with the objective of developing appropriate governance frameworks and guidelines for the use of AI in these fields. Ultimately, the research supports the adaptation and optimisation of accounting and auditing practices and policies in line with technological progress, with the aim of maximising the advantages offered by artificial intelligence.

Although the existing literature on artificial intelligence in accounting and auditing is extensive, several gaps remain. First, conceptual contributions are often separated from applied ones, and the specific functional and architectural characteristics of available AI tools are rarely compared in a structured manner (Hasan, 2022; Kommunuri, 2022). Second, the literature does not clearly distinguish how AI adoption differs according to entity size, although the operational needs and resources of small and medium-sized entities (SMEs) and large companies differ substantially (Lee and Tajudeen, 2020; Fedyk et al., 2022). Third, the question of trustworthiness, that is, the extent to which an AI system can produce correct answers across all possible accounting and audit scenarios, is generally treated as a simple error issue, rather than as a constitutive feature of probabilistic models that can only be tested empirically and cannot be confirmed in absolute terms (OECD, 2023; ICAEW, 2023).

Building on these gaps, the study formulates three research questions:

(RQ1) What are the dominant themes, conceptual structures, and methodological orientations in the recent literature on artificial intelligence in accounting and auditing?

(RQ2) Through which functional categories and architectural choices are AI systems currently embedded in accounting and audit workflows, and how do these patterns vary according to entity size?

(RQ3) What are the trustworthiness limits of current AI tools for accounting and audit, and what implications do these limits have for professional responsibility and for emerging regulatory frameworks?

The main objective of this study is to examine the role and applications of artificial intelligence in accounting and auditing by integrating bibliometric analysis with an exploratory assessment of AI-based solutions used in practice.

To achieve this objective, the study pursues the following specific objectives:

(O_1) Identifying and mapping the main research directions, thematic clusters, and conceptual structures in the literature on artificial intelligence in accounting and auditing;

(O_2) Systematisation of the key concepts, typologies, and technological components of artificial intelligence relevant to financial and audit processes;
(O_3) Analysis of the functional characteristics and application areas of selected AI-based solutions currently used in accounting and auditing practice;
(O_4) Evaluating the operational and organisational implications of AI adoption, with a focus on efficiency, data processing capabilities, and the transformation of professional roles;
(O_5) Integrating the bibliometric and applied findings into a coherent comprehensive perspective on the role of artificial intelligence in accounting and auditing systems.

2. Methodology

The current state of knowledge in the field of artificial intelligence in accounting and auditing was investigated through a mixed-method literature analysis of the relevant literature, combining bibliometric analysis with the selection of the most relevant articles in order to provide a comprehensive understanding of the topic (Hasan, 2022; Leitner-Hanetseder et al., 2021).

First, a bibliometric analysis is conducted to identify the main research directions, thematic clusters, and conceptual developments in the literature on artificial intelligence in accounting and auditing. Second, an applied analytical component is introduced, consisting of a structured examination of AI-based solutions currently available on the market. This component does not follow a traditional case-study design based on primary data collection, but rather adopts a comparative and exploratory perspective, focused on the functional capabilities, application areas, and technological characteristics of selected systems. The integration of these two components allows the study to connect theoretical developments with practical implementations. To conduct the bibliometric analysis, the Web of Science platform was used, and the database was principal search terms, the main phrases of interest, particularly *artificial intelligence* and *accounting*. The initial search returned a total of 14,145 results. Specific filters were subsequently applied, including publications after 2015 (9,146 results), articles only (4,716 articles), articles in English only (4,599 articles), articles within the categories of computer science and business economics (2,110 articles), and articles focused on artificial intelligence and machine learning, software engineering, economics, and robotics (729 articles) (Kokina and Davenport, 2017; Lehner et al., 2019).

By applying these filters, a total of 729 articles were identified. Information on the title, abstract, and authors of these articles was exported into a .txt file, which was subsequently imported into VOSviewer to perform keyword co-occurrence analysis. As illustrated in the figure below, the most relevant keywords—also guiding the present study—are: *artificial intelligence, deep learning, machine learning, performance, classification,* and *model* (Lee and Tajudeen, 2020; Kommunuri, 2022).

The screening process followed a four-stage logic similar to the PRISMA framework (Page et al., 2021). At the identification stage, the Web of Science query returned 14,145 records. At the screening stage, the post-2015 filter retained 9,146 records, the document type filter (articles only) retained 4,716 records, and the language filter (English) retained 4,599 records. At the eligibility stage, two thematic filters were applied: the subject categories were narrowed to computer science and business economics (2,110 records), and the corpus was further restricted to articles focused on artificial intelligence and machine learning, software engineering, economics, and robotics (729 records). At the inclusion stage, the resulting 729 records formed the bibliometric sample. The choice of 2015 as the lower bound is explained by two considerations: it marks a measurable acceleration in AI publications in accounting and auditing journals (Fedyk et al., 2022; Lee and Tajudeen, 2020), and it predates the consolidation of deep learning techniques in commercial financial software (Kommunuri, 2022). The English-only filter was applied to ensure consistent keyword extraction in VOSviewer, since multilingual abstracts tend to fragment co-occurrence clusters and reduce the comparability of thematic maps.

The exploratory component, presented in Section 6, complements the bibliometric analysis with a structured comparison of ten AI-based solutions used in accounting and auditing. The selection covers vendors that combine market visibility (presence in audit and accounting practice) with publicly available technical documentation, so that functional capabilities, data inputs, and integration patterns can be verified against vendor materials rather than inferred. Each solution was characterised across five dimensions: functional category (data capture, transactional processing, analytics and audit support), AI techniques disclosed by the vendor, type of entity typically targeted (SME or large entity), integration mode (standalone, embedded module, API), and references to trustworthiness or governance features (explainability, audit trail, alignment with the EU AI Act or ISO/IEC 42001). The comparative table is presented in Section 6 and supports the cross-cutting interpretation in the discussion.

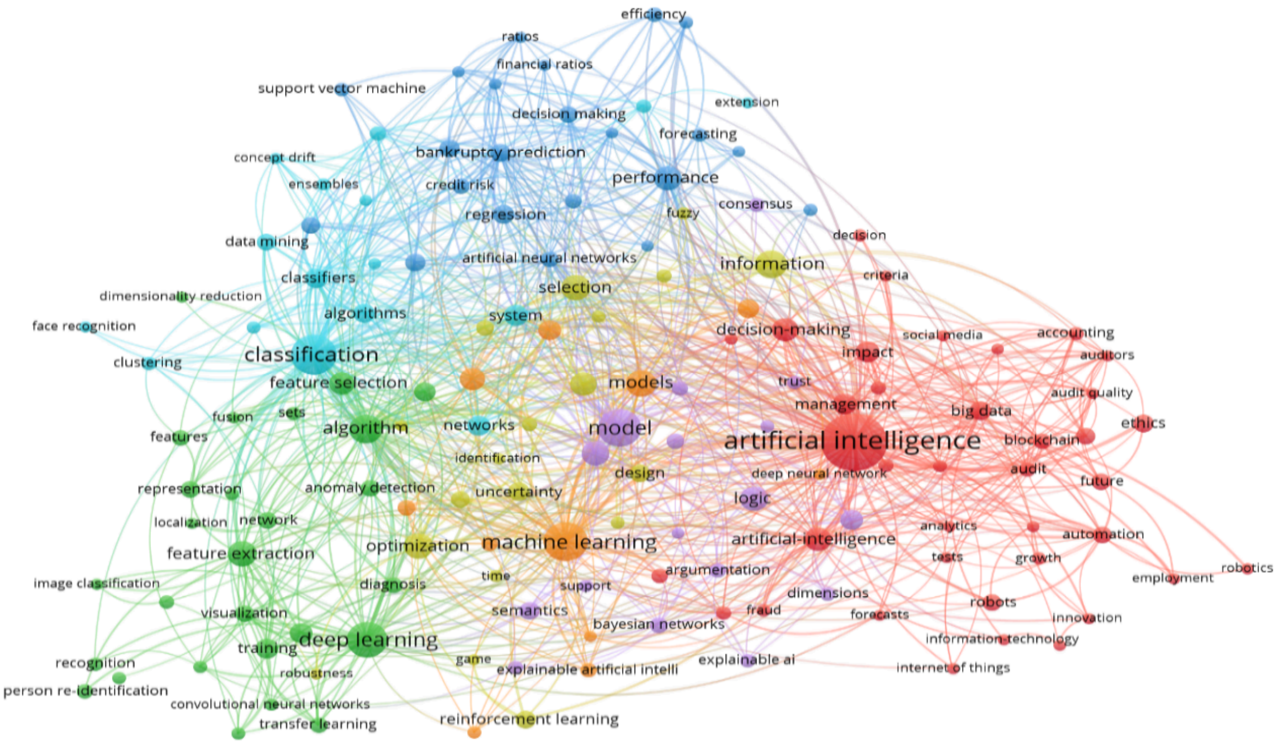

Figure 1. Keyword co-occurrence map generated in VOSviewer from the 729 Web of Science articles (post-2015). Node size reflects the frequency of each term in the corpus, the connecting lines represent co-occurrence between keywords in article abstracts, and colours indicate thematic clusters identified by VOSviewer. Source: authors' processing of Web of Science records in VOSviewer

Following this stage, the most relevant articles were selected through an analysis of their abstracts. This selection enabled the identification of various theories and perspectives discussed in the literature, providing a detailed view of the evolution and trends in the use of AI in accounting (Gambhir and Bhattacharjee, 2021; Chukwuani et al., 2020). The following paragraphs present some of the most relevant ideas and future research directions identified in recent studies.

3. Artificial Intelligence – Concepts and Typologies

This section explores the theoretical foundations of artificial intelligence, beginning with the definition of the concept and the types of artificial intelligence, followed by the technologies and algorithms employed, commonly referred to in IT as subsets of artificial intelligence (Loebbecke and Picot, 2015; Moll and Yigitbasioglu, 2019).

3.1. Basic Aspects of Artificial Intelligence

3.1.1. Definition of Artificial Intelligence

Artificial intelligence is an interdisciplinary field focused on the development of technologies that enable computers to simulate human intelligence. In general terms, artificial intelligence refers to the ability of a machine to imitate human cognitive processes such as learning, reasoning, and perception (Hasan, 2022; Kommunuri, 2022). The OECD (2023) defines an artificial intelligence system as a machine-based system that, for a given set of human-defined objectives, can make predictions, recommendations, or decisions influencing real or virtual environments.

3.1.2. Types of Artificial Intelligence

Artificial intelligence can be classified according to its level of development into three main categories. Weak, or narrow, artificial intelligence (ANI) refers to systems designed to perform specific tasks within a limited scope. These systems operate strictly within their predefined functions and cannot extend beyond their original purpose. As a result, ANI does not reproduce human intelligence in a general sense but instead imitates particular behaviours associated with specific tasks (Shaffer et al., 2020). Strong, or general, artificial intelligence (AGI) represents a more advanced form, characterised by the ability to simulate human cognitive processes across a wide range of activities. In this form, AI would outperform human intelligence across all domains, including reasoning, problem-solving, and decision-making (Shaffer et al., 2020).

3.1.3. Technologies and Algorithms Used in Artificial Intelligence

Technologies and algorithms in artificial intelligence are in continuous development, reflecting the rapid evolution of computational methods and data-processing capabilities. At present, several core subsets define the practical implementation of AI across domains.

Machine learning represents a fundamental approach through which systems learn patterns directly from data without being explicitly programmed for each task. It is widely applied in areas such as image recognition, speech processing, and data classification (Lee and Tajudeen, 2020). Closely related to this approach , neural networks consist of interconnected computational models inspired by the structure of the human brain, enabling the processing of complex information. These models are commonly used for tasks such as image and speech recognition, as well as predictive analytics (Gambhir and Bhattacharjee, 2021).

Deep learning extends this paradigm by employing highly complex, multi-layered neural networks capable of extracting intricate patterns from large datasets. This approach is particularly effective in domains that require advanced data interpretation, including image analysis, speech recognition, and classification tasks (Hasan, 2022). Another important subset is natural language processing, which focuses on enabling machines to understand, interpret, and generate human language. Its applications include machine translation, text analysis, and conversational agents such as chatbots (Kommunuri, 2022).

In addition, genetic algorithms provide optimisation techniques inspired by the principles of biological evolution, where solutions evolve iteratively to reach optimal or near-optimal outcomes. These methods are often applied in complex system design and optimisation problems. Finally, robotics represents a domain where artificial intelligence is integrated into physical systems. Through the coordination of components such as sensors, actuators, and control mechanisms, AI enables robots to perform complex tasks in dynamic environments (Jędrzejka, 2019).

This section provided an introduction to the theoretical foundations of artificial intelligence. It presented a definition of AI, its main types, and its core subsets. It also discussed key technologies and algorithms, including machine learning, deep learning, neural networks, natural language processing, genetic algorithms, and robotics. This serves as a necessary foundation for understanding how artificial intelligence can be applied in accounting and auditing (Fedyk et al., 2022; Noordin et al., 2022; Tiron-Tudor and Deliu, 2022).

4. Artificial Intelligence in Accounting and Auditing

This section examines the ways in which artificial intelligence can represent important support in accounting and auditing. It will discuss the tasks most suitable for AI to take over in the field of accounting and auditing and the cooperation between humans and machines in this context and, based on the studies that have been reviewed, will offer a view on the skills and responsibilities that professionals will have in the future in the context of this human–machine cooperation (Leitner-Hanetseder et al., 2021; Tiron-Tudor and Deliu, 2022; Hasan, 2022).

Today, both in finance and in accounting, the work carried out by finance professionals can no longer be reduced only to paper, pencil, and a chart of accounts. The multitude of transactions, as well as their high degree of complexity, compels professionals to evolve and to find support in new cognitive technologies (Kommunuri, 2022; Moll and Yigitbasioglu, 2019).

AI is the most common cognitive technology, being able to perform tasks ranging from ordinary, repetitive tasks associated with weak AI to complex tasks. Technological transformation, in turn, implies continuous adaptation to change and the permanent updating of knowledge, not only of that knowledge related to the main field of interest (Gambhir and Bhattacharjee, 2021; Shaffer et al., 2020).

4.1. AI-based Algorithms Applicable in Accounting and Auditing

A new symbiosis between humans and machines seems to be taking shape in the future of accounting teams, characterised by networks, openness, flexibility, and interdisciplinary thinking (Leitner-Hanetseder et al., 2021). Subsets of artificial intelligence such as machine learning, robotic process automation, artificial neural networks, and deep learning already find applicability today both in accounting and in auditing. Through them, accounting, finance, audit, and advisory services will be transformed in a substantial way (Kokina and Davenport, 2017; Jędrzejka, 2019; Moffitt et al., 2018; H2O.ai, 2023a).

4.1.1. Machine Learning

Machine learning (ML) uses statistical methods to learn from data and applies algorithms to solve problems specific to the profession. ML is classified into several types, including supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning, while algorithms may be grouped into classifiers, regression, and clustering models (Hasan, 2022; Medium, 2023).

ML algorithms can be used to categorise and interpret digitised data without the need for human help and to record them in the appropriate accounts. The use of ML applications in accounting- and finance-related functions is growing rapidly and they are becoming essential tools in these fields, although they are still relatively new in accounting (Lee and Tajudeen, 2020; Chukwuani et al., 2020; USM Systems, 2023).

By applying ML in audit engagements, more accurate estimates of losses are obtained than those made by managers, which increases the reliability and consistency of those estimates. This is considered one of the most promising advanced technologies used in auditing, because it helps auditors assess complex accounting estimates. Some prior studies have used ML to analyse financial statements, measure information content, and predict errors and irregularities (Fedyk et al., 2022; Noordin et al., 2022; Kokina and Davenport, 2017).

4.1.2. Robotic Process Automation

Another important AI-related automation technology is Robotic Process Automation. RPA systems are used to automate and accelerate laborious tasks such as data validation, database access, creation of relevant documents, and uploading data into storage locations. Standard activities related to audit datasets will be replaced by RPA, which requires little programming. The use of RPA reduces data-processing time and costs and improves process accuracy, consistency, traceability, and the quality of decisions (Jędrzejka, 2019; Moffitt et al., 2018; Power Platform, 2023).

Some tasks in the auditing field can be performed more efficiently by algorithms than by humans, such as loading, cleaning, processing, and analysing data, organising the audit, preparing risk assessments, carrying out audit tests and procedures, as well as preparing working papers, audit files, and related documentation. It can also verify, remove duplicates, and clean data. RPA facilitates revenue reconciliations and their comparison with audited revenues from the previous year, generating alerts when differences exceed materiality thresholds (Moffitt et al., 2018; Jędrzejka, 2019; KPMG, 2023).

4.1.3. Artificial Neural Networks

Another useful AI subset used in accounting is ANN, or Artificial Neural Networks, a powerful method for analysing complex information. ANN learning comes much closer to human performance, improving the efficiency of information systems. ANNs can solve complex problems, make market forecasts, and analyse financial statements, demonstrating considerable analytical potential. They can perform analytical reviews and use algorithms for risk assessment and classification (Hasan, 2022; Kommunuri, 2022; H2O.ai, 2023a).

4.1.4. The Human-in-the-Loop Model

Human-in-the-Loop (HITL) is an AI model that adjusts and learns continuously through feedback provided by humans. The HITL-based AI model ensures continuous human supervision and intervention where necessary in order to correct deficiencies or anomalies not detected by the algorithm. Tiron-Tudor and Deliu (2022) propose the AI model based on HITL as the most suitable for the digitalisation of the audit process so that it reflects as faithfully as possible the human rigour required in auditing.

4.2. Human–Machine Cooperation in the Accounting and Auditing Context

4.2.1. Human–Machine Cooperation in the Accounting Context

AI-based solutions have become increasingly present and widely used in our lives, managing to change the way we live our lives. In accounting, solutions such as blockchain, integrated systems, cloud solutions, robotic process automation, and AI have changed and continue to change the accounting process. The processing of large quantities of data allows systems to provide accuracy, timeliness, and efficiency, and decisions can be made on the basis of the most recent operations, without the risk that the transactions of the current month remain unprocessed, as sometimes happens in the case of traditional software systems (Lehner et al., 2019; Lee & Tajudeen, 2020; Power Platform, 2023).

Present-day accounting is automated, indeed, yet one may refer to the implementation of AI in the accounting process at present as a step just as large as the transition from paper to current accounting software. AI is a general term under which technology can think, learn, perform tasks insightfully, and imitate human intelligence. It is the science and engineering of making intelligent machines and embedding human intelligence into machines (Kommunuri, 2022; McCarthy, 2007).

An article cited by *CPA Australia* indicates that technologies such as AI and RPA can take the accounting profession into a completely new and challenging area. Rapid data processing and the automation of well-defined and repetitive tasks, such as bank reconciliations and supplier invoice processing, will move into the background on the list of professionals' priorities, allowing them to concentrate their attention and know-how on activities with much greater intellectual value (Rollins, 2020; CPA Canada, 2023; Dext, 2023). Major firms such as PwC, KPMG, and Ernst & Young are expected to invest substantial resources in developing AI- and ML-based products and services for their clients by 2026 (Maurer, 2021; EY, 2023; KPMG, 2023).

The complementarity between artificial intelligence and human intelligence is very important and must be maintained, because human intelligence will provide direction and will adapt to new requirements, while artificial intelligence will take over repetitive and tedious tasks, without omissions and without fatigue (Tiron-Tudor and Deliu, 2022; Rollins, 2020). Lee and Tajudeen (2020) observe that artificial intelligence is used not only by large companies through accounting software integration, but also for the electronic archiving of invoices and automated data extraction. Although the AI-driven digital transformation of accounting remains at an early stage, Lehner et al.

(2019) suggest that ongoing developments may lead towards increasingly automated accounting systems. In this context, the core of such systems may consist of multifunctional deep learning networks capable of supporting knowledge and decision-making processes, handling both structured and unstructured data, and providing relevant information for financial analysis (Lehner et al., 2019; H2O.ai, 2023b).

It is also necessary to continue studying the new requirements, tasks, and skills implied by the changes brought by the digital transformation of accounting (Gambhir and Bhattacharjee, 2021; Shaffer et al., 2020). CPA Canada (2023) suggests a series of activities that may easily be replaced by AI, such as basic bookkeeping, receivables collection and short-term liabilities payment processing, payroll entry, and taxation. In clear terms, not only rudimentary and repetitive accounting activities can be taken over, but even highly complex activities from a cognitive point of view, such as borderline decisions grounded in very high responsibility (Kommunuri, 2022; Leitner-Hanetseder et al., 2021).

4.2.2. Human–Machine Cooperation in the Auditing Context

In general, collecting information for the audit file is done by extracting samples from the available dataset. Under such conditions, it may be difficult for auditors to detect irregularities, and certain anomalies may remain unidentified (Fedyk et al., 2022; Noordin et al., 2022).

AI-based algorithms improve audit processes through their integration into digital workflows and through the way in which they perceive and understand the increasingly digitalised businesses of clients. The field of auditing is considered particularly suitable for studying the effects of this technology (Kokina and Davenport, 2017; Tiron-Tudor and Deliu, 2022). AI-based systems facilitate numerous audit processes, from entering and examining all data to minimising errors, detecting fraudulent records, and reporting them (Noordin et al., 2022; Fedyk et al., 2022; CaseWare, 2023).

AI takes over and performs repetitive tasks based on well-defined rules much faster and more efficiently. In this context, the work of the auditor reaches a high level of quality because the time allocated to data preparation can be used for deeper risk analysis and for identifying solutions to avoid these risks (Fedyk et al., 2022; Moffitt et al., 2018). The collection, validation, and analysis of data in the audit process represent demanding work that the auditor has had to carry out for decades, deviating at times from the main purpose of the audit process, namely identifying risks and offering solutions to reduce them (Kokina and Davenport, 2017; Noordin et al., 2022).

An ACCA report also shows that rudimentary data-entry activities may no longer fall among the responsibilities of accountants, allowing them to focus their attention and expertise on consulting, advice, and business support (Rollins, 2020). AI technology applied throughout the audit process may generate significant benefits, as artificial intelligence can analyse the entire transactional population rather than relying solely on statistical sampling, thereby providing a more comprehensive view of a company's transactions (Fedyk et al., 2022; KPMG, 2023).

A main reason for the popularity of the desire to implement AI in auditing is that data entry and analysis could be performed by AI, making audits more efficient and more cost-effective. In addition, auditing is not a field of approximations but one with a high degree of accuracy, based primarily on the most correct data possible, where the absence of errors is essential (Fedyk et al., 2022; Tiron-Tudor and Deliu, 2022). Auditors should not look at algorithms with fear, but should understand that they are tools that continuously improve themselves and that can ease and streamline the activities undertaken by them (Kokina and Davenport, 2017; Tiron-Tudor and Deliu, 2022).

A study conducted by Fedyk et al. (2022) based on 17 interviews involving the eight largest public accounting firms in the United States, with nine Big Four representatives participating, reveals several important aspects regarding the implementation of AI in the audit process, such as the following: AI is widely implemented in audit processes, the centralisation of AI is very well developed at all levels, and AI fulfills its main objectives regarding fraud and anomaly detection, risk assessment, and the redirection of human attention towards complex issues.

All the interviewed companies use technologies such as RPA, data analytics,and AI-based systems. Some interviewees considered the use of drones useful in fields such as agriculture or timber inventories, and one Big Four participant states that drones are effectively used in the audit process. Investments in AI made by auditors are reflected much more in audit quality than investments in AI made by clients (Fedyk et al., 2022).

The twenty-first century is considered the age of automation, and accounting is one of the fields in which automation may find wide applicability. From recording transactions to interpreting data, automation may find its place in the accounting process. Very smart companies have captured both the possible benefits brought by AI and the uncertainty surrounding it, and have turned the technology into a highly competitive advantage in the market (Chukwuani et al., 2020; Kommunuri, 2022; EY, 2023).

Also, all the companies whose representatives took part in the interview use AI technology, for example in the detection of errors and fraud through machine learning, order/invoice matching, mapping of cash-collected receivables, financial risk assessment, anti-money laundering, contract review, and the analysis of large datasets, and they feel pressure that forces them to move towards new technologies, pressure resulting from the high expectations of their clients. Quite often, clients themselves request the implementation of AI technologies in order to increase confidence in the quality and reliability of the audit provided (Fedyk et al., 2022; EY, 2023).

Audit firms are able to increase the value of the services they provide, adapt to change, use new technologies to their advantage, and optimise their costs. The results show that the fees of audit firms that have employees in the AI field decline by up to 2.1% over three years; also, the number of employees in the economic area of audit firms would decline by up to 7.1% over four years. All these cost reductions are the result of AI implementation (Fedyk et al., 2022).

Data analysis is an excellent means through which AI manages to increase audit quality, through the detection of errors and fraud, a deep understanding of the operations carried out, and of the entity's risks (Fedyk et al., 2022; Noordin et al., 2022). All the persons interviewed observe beneficial effects of AI in the audit process, from quality to efficiency. The use of artificial intelligence in auditing improves its quality and efficiency, reducing costs and diminishing the need for labour, especially entry-level employees (Fedyk et al., 2022; Noordin et al., 2022). The higher quality of audits carried out with the help of artificial intelligence has been identified precisely through the lower level of corrections and restatements. Another significant advantage of AI in the audit process is that the audit is performed on time, with high precision (Fedyk et al., 2022).

AI implementation is not simple, because there must be very close collaboration between IT specialists and those in the economic field. Companies such as the Big Four prefer to develop software algorithms internally and to purchase programming services, obtaining an AI-based solution that is tailored and perfectly aligned with the company's needs. Smaller firms, by contrast, tend to invest in externally developed software solutions. Even so, the greatest obstacle remains employee training in the use of these technologies; software development is the easy part, while implementation and scaling may take years (Fedyk et al., 2022; Shaffer et al., 2020).

Accounting standard setters, professional accounting bodies, academics, and practitioners must focus on revising and updating existing accounting guidance and standards in order to respond to the requirements and challenges of the AI era (Salawu and Moloi, 2020; Gambhir and Bhattacharjee, 2021). AI brings changes in the structure of the workforce, and the main impediment is represented by staff training regarding AI adoption. It has also found that among the three experience categories—junior, mid-level, and senior—only the junior-level show a reduction in the number of jobs, by up to 5.7% over three years (Fedyk et al., 2022).

Insufficient qualification of employees may represent a serious obstacle in the implementation of AI-based technologies, and human–machine collaboration will be successful in the future (Leitner-Hanetseder et al., 2021; Shaffer et al., 2020). Not only AI implementation will generate costs for companies, but also the training of employees through development programmes. Education, in turn, should revise its programmes and courses in order to satisfy current market demand (Gambhir and Bhattacharjee, 2021; Shaffer et al., 2020). Likewise, the educational programmes of specialised institutions should be revised in order to adapt to the new requirements in this field. Many universities have begun this reform of educational programmes by adding courses in information technology, data analysis, cybersecurity, and database management (Gambhir and Bhattacharjee, 2021; Leitner-Hanetseder et al., 2021).

In conclusion, the use of artificial intelligence in accounting and auditing can bring benefits, improving efficiency, precision, and the quality of financial information. At the same time, certain disadvantages and risks must also be considered, such as high initial costs and data security risk (Noordin et al., 2022; Salawu and Moloi, 2020; EY, 2023).

4.3. A View on Future Professions in the Accounting Field

4.3.1. Emerging Professional Competencies

Accounting firms can increase their value by offering much higher-quality services to clients. Client support remains essential, particularly for organisations that may lack a comprehensive understanding of their own operational and financial processes. Accountants and auditors who will understand and use artificial intelligence in their work will not only maintain their position in the market, but will even prosper and will be able to enjoy many more clients (Leitner-Hanetseder et al., 2021; Gambhir and Bhattacharjee, 2021).

It is expected that younger generations will adapt more easily to technological change. The greater challenge may arise for senior accountants,however work will become easier, and the possibility of losing one’s job for professionals who accept technology will be much lower (Shaffer et al., 2020; Leitner-Hanetseder et al., 2021). A study carried out on 84 employees from organisations in the United Arab Emirates, holding junior, mid-level, and top-management positions in audit firms, banks, education, and retail, manages to outline the responsibilities of the future accounting employee (Noordin et al., 2022).

In the future, the most in-demand skills for mid-level and senior positions will include data analysis and the use of related tools. Senior functions will focus more on understanding and analysing data. Junior and mid-level positions could face unemployment, especially because AI technology will take over their responsibilities to a large extent (Leitner-Hanetseder et al., 2021; Fedyk et al., 2022).

There is a series of standard skills that an accounting or auditing professional must possess as part of professional development. The following competencies are particularly relevant:

- **professional skills** – these skills must always remain current, in order to provide optimal solutions to clients’ problems (Gambhir and Bhattacharjee, 2021);
- **management skills** – these are of major importance when speaking about coordinating a financial-accounting department or the entire financial-accounting activity of a company (Leitner-Hanetseder et al., 2021);
- **IT skills** – these skills are necessary even now, because the input and supervision of transactions are carried out with the help of accounting software, and in the future they will be mandatory in order to understand the processes carried out by AI and to correct them where needed (Shaffer et al., 2020; Gambhir and Bhattacharjee, 2021);
- **analytical skills** – these are skills of synthesis and of extracting relevant information from economic transactions (Leitner-Hanetseder et al., 2021);
- **decision-making skills** – these involve the efficient evaluation of data and circumstances in order to propose optimal solutions that guide activity towards performance (Gambhir and Bhattacharjee, 2021).

4.3.2. Changing Roles and Responsibilities

An applied study carried out on 138 interviewees reveals the implications that technology will have over the next ten years for several occupations in the accounting field, such as bookkeeper, financial accountant, controller, data analyst, treasurer, and financial systems and processes manager (Leitner-Hanetseder et al., 2021).

Each of the positions listed above will undergo certain changes, whether speaking of changes in responsibilities and objectives or of changes in demand for certain positions (Leitner-Hanetseder et al., 2021).

Bookkeeper

Demand for the bookkeeper job is expected to decrease drastically, being much lower ten years from now. However, this job will not disappear but will undergo a change in responsibilities. The bookkeeper will have to ensure that all transactions are accounted for intelligently, and intervention will take place only in special cases, where there is no other possibility for solving the problem (Leitner-Hanetseder et al., 2021; Shaffer et al., 2020).

Financial accountant

The tasks of the financial accountant will not be as easy to replace as those of the bookkeeper. As technology advances, so do the regulations that a financial accountant must take into account and reconcile with the activity of each client, an activity that itself advances and innovates continuously. AI solutions will make the work of the financial accountant easier, but responsibility for the statements prepared will still belong to the accountant. Also, the accountant will be able to accept decisions proposed by the virtual AI assistant but will have to assess whether the decision complies with ethical principles and the accounting standards applied (Salawu & Moloi, 2020; Leitner-Hanetseder et al., 2021).

Controller

In accounting based on artificial intelligence, the role of the controller changes, becoming that of a business partner. Controllers are no longer only providers of information but also consultants who use data-analysis skills to draw conclusions relevant for the business. Digitalisation and digital technologies have an impact on controllers, who must develop skills in data analysis and visualisation, as well as in understanding artificial intelligence. By using these technologies, controllers can make management reporting, process optimisation, and strategic planning more efficient, contributing to the organisation's success (Leitner-Hanetseder et al., 2021; Moll & Yigitbasioglu, 2019).

Data analyst

The business data analyst is responsible for data analysis and visualisation in accounting. Presentation and communication skills are not the most important for the business data analyst; more important are analytical thinking and innovation (Leitner-Hanetseder et al., 2021).

In an AI-supported accounting environment, the data analyst role evolves along three operational lines. First, the analyst designs and maintains data pipelines that feed AI models with reconciled transactional data, working closely with controllers and IT teams to ensure that source-system mappings remain consistent over time (Moll and Yigitbasioglu, 2019). Second, the analyst is expected to interpret model outputs (anomaly scores, predictive ranges, classification confidence) and translate them into accounting and audit narratives that managers and auditors can act upon, which requires statistical literacy beyond standard reporting tools (Kommunuri, 2022; Fedyk et al., 2022). Third, the analyst contributes to the validation and monitoring of AI components: detecting data drift, verifying that retraining cycles preserve model behaviour, and documenting decisions for internal control and external assurance purposes, in line with the trustworthiness requirements of the EU AI Act (European Parliament, 2024) and ISO/IEC 42001 (ISO, 2023). Compared with a traditional reporting analyst, the AI-aware analyst combines accounting domain knowledge with data-engineering and model-governance competencies, and is positioned as the connecting layer between technical teams and the financial function.

Treasurer

Treasury and risk management become more and more important for a company's success, because of the growing use of big data, continuously changing economic conditions, and new financing instruments that appear (Moll & Yigitbasioglu, 2019; Leitner-Hanetseder et al., 2021). The tasks of treasurers and risk managers have changed in recent years, because they must possess general skills regarding liquidity and adapt to legal developments and reporting obligations. The use of integrated treasury-management systems and AI technology is becoming increasingly necessary in order to predict regulatory actions and verify compliance (Leitner-Hanetseder et al., 2021).

The complexity of tasks has increased and represents an unknown level of operational risks. Treasurers and risk managers face challenges related to understanding and managing technological complexity, as well as to communication with authorities. At the same time, this complexity also brings benefits, such as the need to be open to technology and to update competencies constantly, as well as to combine business knowledge, technological skills, and communication skills in order to succeed in the field (Leitner-Hanetseder et al., 2021).

Financial systems and processes manager

The financial systems and processes manager plays a central role in selecting and implementing AI-based technologies within the finance and accounting department. The manager must coordinate digitalisation and automation efforts, identifying the right processes for the implementation of AI-based technology and ensuring their effectiveness and compliance. In addition to technical skills, the financial systems and processes manager must also have communication skills, a holistic understanding of processes, accounting knowledge, and project-management skills in order to successfully lead digital transformation and collaboration between people and AI-based technology (Leitner-Hanetseder et al., 2021).

4.4. The Transformation of Accounting Through Technologies Based on Artificial Intelligence

Technologies based on artificial intelligence have transformed many aspects of accounting activities, contributing to process efficiency and to improving the quality of accounting reporting. These innovative technologies have been widely adopted in industry and have brought numerous benefits, especially in relation to speed, accuracy, and the capacity to process large volumes of data (Chukwuani et al., 2020; Kommunuri, 2022).

In practice, artificial intelligence is implemented through several interconnected applications that support accounting processes. For example, in the context of B2B transactions, trading processes and data exchange between companies become faster and more accurate, reducing human error and increasing operational efficiency (Moll and Yigitbasioglu, 2019). At the same time, digitised data exchange enables the rapid and secure transfer of information between different parties involved in the accounting process, contributing to transparency and reducing the risk of inconsistencies (Lehner et al., 2019).

An important contribution is provided by Optical Character Recognition (OCR) technology, which allows the conversion of physical documents, such as invoices, into digital format. This facilitates faster access to information and reduces the time required for manual data entry, while also minimising the risk of errors (Lee and Tajudeen, 2020; Dext, 2023; H2O.ai, 2023b). In a similar direction, digitised invoices and automated data capture further streamline accounting workflows and improve data accuracy.

Artificial intelligence also supports the classification and interpretation of financial data. Algorithms can analyse patterns and characteristics within datasets and automatically assign transactions to the appropriate accounts, ensuring consistency in recording and reducing the need for manual intervention (Lee and Tajudeen, 2020; Hasan, 2022). In addition, intelligent automation systems are increasingly used in accounting activities, performing tasks such as account reconciliation and data verification. These systems are capable of processing large volumes of information in a shorter time than human operators, contributing to faster and more reliable operations (Jędrzejka, 2019; Power Platform, 2023).

Another important aspect concerns data governance and transparency. The use of permissions over digitised data allows controlled access to information, supporting audit transparency and traceability (KPMG, 2023). At a more advanced level, technologies such as drones and the Internet of Things enable the rapid collection and analysis of data regarding assets and liabilities, supporting more accurate valuation and reporting processes (Fedyk et al., 2022).
Artificial intelligence also plays a role in supporting decision-making. Natural language processing and expert systems can analyse textual and numerical data, offering recommendations that assist accountants and managers in complex situations (Kommunuri, 2022; Hasan, 2022). In addition, Business Intelligence tools provide the ability to analyse data, identify patterns and trends, and generate relevant insights, supporting more informed and efficient decisions (IBM, 2023; Domo, 2023).

4.5. Exploring the Potential of AI Applications in the Field of Accounting

Artificial intelligence applications offer valuable opportunities for automating repetitive tasks and for supporting decision-making processes in accounting. Their role is not limited to efficiency gains but also extends to improving the accuracy and relevance of financial information (Chukwuani et al., 2020; Kommunuri, 2022).

One of the most visible applications is in invoicing and invoice management, where AI systems can automate the extraction and verification of data from invoices. This reduces human error and accelerates processing, contributing to more reliable financial records (Lee and Tajudeen, 2020; Dext, 2023; H2O.ai, 2023b). In a similar manner, artificial intelligence can support the process of adding and verifying suppliers by automatically checking the information provided and ensuring compliance with procurement policies, thus reducing the risk of fraud (Kommunuri, 2022; USM Systems, 2023).

AI also contributes to procurement processes by analysing purchasing patterns and generating recommendations for supply and reordering. This leads to better resource management and cost optimisation (Moll and Yigitbasioglu, 2019). In the auditing area, AI enables the automatic analysis of transactions and accounting records, facilitating the identification of discrepancies or anomalies and improving the overall quality of audit procedures (Fedyk et al., 2022; Noordin et al., 2022; CaseWare, 2023).

Another important application is cash-flow tracking, where artificial intelligence can analyse historical data and external factors in order to generate forecasts and support financial planning (Kommunuri, 2022). Expense management is also improved, as AI systems can correlate expenses with production levels, identify cost patterns, and support better control over financial resources (Chukwuani et al., 2020).

Finally, AI-based chatbots provide support in everyday accounting activities by answering frequent questions, offering financial information, and guiding users in solving specific problems. These tools ensure faster access to information and improve interaction between users and accounting systems (Kommunuri, 2022; Hasan, 2022).

5. The Impact of the Use of Artificial Intelligence in Accounting and Auditing

This section examines the impact of the use of artificial intelligence in accounting and auditing. It will discuss the advantages of its use, such as the efficiency and productivity of accounting and audit processes, the identification of risks and issues, and the improvement of the quality of financial information. It will also examine the disadvantages and challenges of the use of artificial intelligence in accounting and auditing, such as security and data confidentiality risks, excessive dependence on technology, and the possible consequences for jobs and for the accounting and auditing profession, and will discuss the ethical aspects of the use of artificial intelligence in accounting and auditing (Fedyk et al., 2022; Noordin et al., 2022; ICAEW, 2023).

5.1. Advantages of Using Artificial Intelligence in Accounting and Auditing

The implementation of AI in these sectors brings numerous advantages and benefits, redefining the way in which financial information and audit processes are managed. The greatest advantages of implementing AI in the audit and accounting process are the integration of large structured and unstructured datasets in order to obtain a comprehensive representation of the company's financial and non-financial situation and the analysis of these datasets, while the automation of procedures would generate time savings (Fedyk et al., 2022; PwC, 2023a; H2O.ai, 2023a).

Also included among the advantages of artificial intelligence in accounting and finance is its ability to support continuous system development with a reduced likelihood of human error. AI-based systems can operate consistently over time, processing large volumes of data without fatigue, which contributes to higher accuracy and reliability in financial operations (Chukwuani et al., 2020; Dext, 2023).

Another important benefit lies in the reallocation of human effort. By taking over routine and time-consuming tasks, artificial intelligence allows accountants to focus more on analysis, interpretation, and strategic decision-making, rather than on repetitive operational activities (CPA Canada, 2023; Rollins, 2020). This shift contributes to a change in the professional role, moving from execution towards higher-value functions. Artificial intelligence also supports the concept of continuous auditing and improves precision in audit processes. Through automated data analysis and real-time monitoring, AI systems enable more consistent verification procedures and reduce the likelihood of undetected errors (KPMG, 2023; MindBridge, 2023).

In addition, AI enhances real-time visibility over financial data, providing a clearer and more comprehensive view of an organisation's financial position. By integrating and analysing data continuously, these systems support faster and more informed decision-making, allowing organisations to respond more effectively to changing conditions (IBM, 2023; Domo, 2023).

5.2. The Impact of AI Technologies in Accounting and Auditing

Besides the obstacles involved in implementing AI in the audit process, the human acceptance model of artificial intelligence may also represent an impediment. Hassan identifies three types of acceptance as follows: passive acceptance, active acceptance, and sceptical acceptance (Hasan, 2022).

- **Passive acceptance** – people understand the existence of the technology, but do not fully understand its applicability and ignore it;
- **Active acceptance** – people understand the existence and applicability of the technology and use it in order to obtain benefits;
- **Sceptical acceptance** – people are not convinced that the implementation and existence of the technology are possible.

Likewise, social background significantly influences people's perceptions regarding artificial intelligence and its use (Hasan, 2022; OECD, 2023).

The beneficial impact implied by the implementation of artificial intelligence in the accounting and financial industry can be observed across several dimensions, reflecting both operational improvements and broader changes in the role of financial functions.

One important effect is the transition towards new working paradigms, where accounting and finance professionals become more actively involved in business processes and decision-making. Artificial intelligence supports this shift by providing timely and relevant insights, allowing professionals to move beyond routine tasks and contribute more directly to organisational strategy (Kommunuri, 2022; USM Systems, 2023).

At the same time, AI enables the automation of accounting tasks, reducing the time allocated to repetitive activities and allowing human effort to be redirected towards planning, analysis, and growth-oriented initiatives (Chukwuani et al., 2020; Botkeeper, 2023). This contributes to a more efficient use of human resources and a redefinition of professional roles.

Another significant impact is reflected in the acceleration and improvement of closing procedures. Through automated data processing and validation, artificial intelligence allows faster and more accurate financial closing, reducing delays and increasing the reliability of reported information (Sage, 2023; Power Platform, 2023). Artificial intelligence also contributes to the optimisation of accounts payable and receivable processes. By integrating digital workflows and automating data handling, organisations can manage financial transactions more efficiently and reduce errors associated with manual processing (Lee and Tajudeen, 2020; Dext, 2023). In the auditing domain, AI leads to more efficient processes by enabling rapid access to data and improving security through digitalisation. These developments support more effective audit procedures and enhance the overall quality of audit outcomes (CaseWare, 2023; Wolters Kluwer, 2023).

Finally, AI supports the preparation of financial reporting and the proactive adjustment of business strategies. By continuously processing and analysing financial data, these systems allow organisations to respond more quickly to changes and to base their decisions on up-to-date and relevant information (IBM, 2023; Domo, 2023).

The Efficiency and Productivity of Accounting and Audit Processes

The use of artificial intelligence can improve the efficiency and productivity of accounting and audit processes by reducing the time and costs involved and by increasing the accuracy of financial information (Chukwuani et al., 2020; Fedyk et al., 2022; Lee and Tajudeen, 2020).

The closing procedures of certain accounting periods can be difficult, and, for reasons of prudence, the verification of certain journals, VAT, the closing of accounting accounts, the calculation and declaration of taxes and duties, and the preparation of tax returns are required. All these procedures require increased attention, and the accountant may be forced to compress weeks of work into a single week. In this context, AI proves particularly valuable by automating tedious and repetitive tasks, thereby allowing accountants to focus on activities requiring advanced professional expertise (CPA Canada, 2023; Sage, 2023; Power Platform, 2023).

The foundations of auditing, professional judgment, and professional scepticism cannot be replaced by AI. However, auditors who understand its usefulness and who improve certain simple yet time-consuming stages will be able to offer their clients high-quality services with high added value. Those auditors who use AI to their professional advantage will be able to strengthen their position in the audit services market and even expand it (Tiron-Tudor & Deliu, 2022; Fedyk et al., 2022).

Artificial intelligence can help identify risks and issues more efficiently, thereby reducing the risk of fraud or financial errors. At the level of SMEs, it is common to encounter situations in which the entire administrative staff, including finance and accounting, human resources, and secretariat staff, has access both to accounting and to cash flows, and this unrestricted access may increase the risk of financial fraud (PwC, 2023a; EY, 2023). AI does not focus only on the automation of accounting and audit processes but also monitors access to data with the help of fingerprint scanners, retina scanners, and passwords; it also authorises and carries out certain activities only for those individuals who are responsible for them (EY, 2023; ICAEW, 2023). By implementing artificial intelligence, an improvement in the quality of financial information can be obtained through the reduction of human errors and through a more accurate analysis of financial data (Lee & Tajudeen, 2020; Chukwuani et al., 2020).

The process of recording and monitoring each transaction in accounting can consume time and resources and may lead to unintended errors. Artificial intelligence optimises these processes and allows their close supervision by the accountant, with the help of a system that generates alerts when a manually entered transaction contains errors or when suspicious transactions exist. In this way, a superior quality of financial information is ensured, while the risk of human error is eliminated or minimised (MindBridge, 2023; H2O.ai, 2023b).

A higher quality of audits performed with the help of artificial intelligence has been identified precisely through the lower level of corrections and restatements. Another considerable advantage of AI in the audit process is that the audit is performed on time and with high precision (Fedyk et al., 2022; Noordin et al., 2022).

5.3. The Disadvantages and Challenges of Using Artificial Intelligence in Accounting and Auditing

At the same time, several identified disadvantages include potential job losses, which may contribute to a decline in audit quality, as well as risks to financial-data security if sensitive information is accessed by unauthorised parties (Fedyk et al., 2022; Shaffer et al., 2020; ICAEW, 2023).

5.3.1. Data Security and Confidentiality Risks

Financial data are critical and sensitive and must be protected against unauthorised access or manipulation for improper purposes. Artificial intelligence may increase the security and confidentiality risk of financial data precisely because it is a software solution that could become the target of cyberattacks (ICAEW, 2023; EY, 2023).

Cybersecurity cannot be ensured exclusively by accountants themselves, although they may reduce risks by following standard security practices, such as avoiding suspicious emails, using antivirus software, and refusing to connect USB drives, CDs, or other peripherals originating from untrusted sources to computer systems.

Even so, these good practices are not sufficient for preventing security and data-confidentiality risks. The cybersecurity specialist is the professional who can propose the best solutions for avoiding unwanted events, but such expertise implies additional costs that the company must bear (ICAEW, 2023; Salawu & Moloi, 2020).

5.3.2. Excessive Dependence on Technology

Excessive dependence on technology may become a problem because technology can be subject to errors or failures and may require a high level of maintenance and updating (Kommunuri, 2022; ICAEW, 2023). AI systems may also generate significant reputational risks for organisations. By handling large volumes of sensitive data and making critical decisions in fields such as credit, education, employment, and healthcare, there is a risk that a system may be biased, may contain errors, or may be hacked. The use of an AI system for unethical purposes may have consequences for the reputation of the organisation that uses it (OECD, 2023; EY, 2023; ICAEW, 2023).

5.3.3. Possible Consequences for Jobs

The use of artificial intelligence may reduce the need for human labour in certain areas and may have consequences for the accounting and auditing profession, requiring new competencies and skills in order for professionals to remain relevant in their field (Leitner-Hanetseder et al., 2021; Shaffer et al., 2020; Gambhir and Bhattacharjee, 2021).

In conclusion, the use of artificial intelligence in accounting and auditing can bring advantages, such as improving the efficiency, precision, and quality of financial information. At the same time, the use of artificial intelligence may also involve certain disadvantages and challenges, such as risks related to data security and confidentiality, excessive dependence on technology, and possible consequences for jobs and for the accounting and auditing profession (Fedyk et al., 2022; Noordin et al., 2022; ICAEW, 2023).

It is very important to take these aspects into account and to develop adequate strategies in order to maximise the benefits of using artificial intelligence and to minimise the associated risks and challenges. In addition, it is important to promote education and continuous training in order to develop competencies and skills in the field of using artificial intelligence in accounting and auditing (Gambhir and Bhattacharjee, 2021; Shaffer et al., 2020; CPA Canada, 2023).

5.4. The Ethics of Using Artificial Intelligence in Accounting and Auditing

Ethical Principles and Social Responsibility

The use of artificial intelligence in accounting and auditing must be governed by ethical principles such as transparency, accountability, fairness, and integrity. These principles ensure that the use of artificial intelligence is correct and responsible. The proper and ethical use of AI in companies may stimulate innovation and employment growth rather than reduce it (OECD, 2023; Salawu & Moloi, 2020).

The applicability of artificial intelligence in the fields under study may lead to decisions that affect people and companies. Therefore, it is essential to pay attention to ethical aspects in making decisions related to the use of artificial intelligence in accounting and auditing (Tiron-Tudor & Deliu, 2022; OECD, 2023). The implementation of artificial intelligence in accounting and auditing must also take social responsibility into account, ensuring that its use is beneficial to society and does not have negative consequences for it (OECD, 2023; ICAEW, 2023).

In conclusion, the use of artificial intelligence in accounting and auditing must be regulated and governed by ethical principles in order to ensure that its use is ethical and responsible. It is important to develop adequate regulations and to promote ethics in the use of artificial intelligence in accounting and auditing, in order to ensure that it is beneficial to society and does not have negative consequences for it (OECD, 2023; Salawu & Moloi, 2020).

5.5. Trustworthiness, Architectural Considerations and Entity-Size Differentiation

In contrast with traditional information systems, where reliability is treated as the absence of errors, trustworthiness in artificial intelligence represents a constitutive feature of the system. The Ethics Guidelines for Trustworthy AI issued by the High-Level Expert Group on Artificial Intelligence (2019) and the EU AI Act (European Parliament, 2024) define trustworthiness as a combination of lawfulness, ethical alignment and technical robustness, supported by seven operational requirements: human oversight, technical robustness and safety, privacy and data governance, transparency, diversity and non-discrimination, societal and environmental wellbeing, and accountability. ISO/IEC 42001 (ISO, 2023) and the NIST (2023) translate these requirements into governance structures and continuous risk-management cycles. In accounting and auditing, where outputs feed regulatory reporting, fiscal decisions and assurance opinions, the implication is that any failure of an AI system is not a marginal defect but a violation of the core service the entity provides to its stakeholders. For this reason, the present study treats trustworthiness as a property to be designed and audited, not as a residual quality measured after deployment.

A second consequence concerns the description of AI systems beyond the black-box label that is often used in the accounting literature. The systems examined in Section 5 follow a layered architecture composed of: (i) a data layer that ingests transactional, document or sensor data, frequently through ERP connectors and OCR pipelines; (ii) a feature engineering and pre-processing layer that normalises and enriches inputs; (iii) a model layer combining supervised, unsupervised and rule-based components, where deep neural networks (as in GL.ai), tree-based ensembles and unsupervised methods (as in MindBridge) or AutoML pipelines (as in H2O AI Cloud) are configured; (iv) a decision-support and explanation layer that surfaces risk scores, anomaly flags or accounting entries with traceability to the underlying transactions; and (v) a governance layer that records access rights, model versions, retraining events and human approvals.

This decomposition allows reviewers to identify where automation occurs, where human judgement remains decisive, and where assurance procedures can be inserted, instead of treating each tool as an opaque artefact.

The third consequence is that AI adoption in accounting and auditing is not uniform across entity sizes. Survey evidence reported by ACCA (2023), ICAEW (2023) and the OECD (2023), together with the bibliometric corpus analysed in Section 3, shows two distinct profiles. Small and medium-sized entities tend to adopt embedded AI features bundled in cloud accounting suites and invoice-capture services (Botkeeper, Dext, Sage Intacct), where the AI component is configured by the vendor and consumed as a standardised service, with limited internal customisation and with trustworthiness controls inherited from the provider. Large entities and Big Four audit firms, by contrast, deploy specialised platforms (MindBridge, Inflo, GL.ai, TeamMate+ Audit, H2O AI Cloud) supported by internal data science teams, internal validation procedures and dedicated governance committees, which allows them to meet the higher trustworthiness expectations of regulated financial reporting. Recognising this asymmetry matters for two reasons: it explains why the same technology produces different operational outcomes in SMEs and in large entities, and it indicates that regulatory instruments such as the EU AI Act, ISO/IEC 42001 and the NIST AI RMF will be implemented through different practical pathways depending on the size and resources of the adopting entity.

6. Exploratory Analysis of AI Applications in Accounting and Auditing

In a context characterised by continuous technological change, digital transformation has become a necessity in most fields of activity, and accounting is no exception. Even so, in accounting practice there are still major challenges related to the efficient processing of invoices and the management of complex financial data. In this context, artificial intelligence represents a promising technological solution capable of improving accounting efficiency, automation, and decision-support processes.

This exploratory study addresses two distinct directions in the use of artificial intelligence in accounting and auditing. The first direction focuses on the need identified in accounting practice for specialised software for invoice processing. This need is generated by the existing challenges in the manual invoice-processing workflow, which involves effort, time, and human error. It focuses on the identification and analysis of additional artificial intelligence–based tools that can facilitate accounting and auditing processes. The selection of software solutions was based on their relevance in professional practice, frequency of use in the literature, and the diversity of functionalities provided (e.g., automation, analytics, predictive capabilities, audit support). Various technologies and applications of artificial intelligence in accounting are examined, together with their impact on operational efficiency and the quality of financial information. Relevant case studies and practical examples of AI implementation in accounting are analysed, and the associated advantages and challenges are evaluated.

The analysed solutions were grouped into three functional categories:

(i) process automation tools,

(ii) data analytics and business intelligence platforms, and

(iii) predictive and audit-oriented AI systems.

The objective of this exploratory study is to provide a clear perspective on how artificial intelligence can improve accounting and auditing processes by optimising workflows, reducing errors, and generating more accurate and relevant financial information to support decision-making within organisations.

The importance of artificial intelligence in accounting is highlighted, and well-founded arguments are presented in support of the implementation and adoption of this technology in modern accounting practice.

The main objective is to facilitate the integration of artificial intelligence into current accounting practice, thereby avoiding its confinement to a purely theoretical or distant perspective.

The implementation of research results in everyday accounting practice is pursued, with the aim of increasing efficiency and reliability and of generating added value for entities operating in the accounting field. It adopts a practical approach to artificial intelligence in accounting, seeking to provide real and applicable solutions in the current context, with the objective of achieving improvements in accounting operations and in the quality of financial information.

6.1. Identification and Analysis of AI-Based Solutions

The following section presents several solutions that illustrate the broad potential of integrating artificial intelligence into accounting, demonstrating how technology can improve efficiency, precision, and value creation in accounting processes and financial decision-making. AI-based solutions are numerous, and for this reason an attempt has been made to group them according to the purpose they serve (Chukwuani et al., 2020; Kommunuri, 2022).

Table 1. Comparative profile of selected AI-based solutions for accounting and auditing

Tool	Functional category	AI techniques disclosed by vendor	Target entity size	Integration mode	Trustworthiness and governance features
Botkeeper	Bookkeeping automation	Machine learning; robotic process automation	SMEs and accounting practices	SaaS platform with human bookkeeper review	Human-in-the-loop review; audit trail of automated postings
Dext	Data capture and document processing	Optical character recognition; supervised learning for line-item extraction	SMEs and small accounting firms	API integrations with Xero, QuickBooks, Sage and similar ledgers	Document-level data lineage; user validation step before posting
Domo	Business intelligence and data analytics	Machine learning; natural language querying of dashboards	Mid-sized and large entities	Cloud BI platform with connectors to ERP, CRM and accounting systems	Role-based access control; data governance and certification workflows
Sage Intacct	ERP with embedded AI features	Machine learning for anomaly detection and workflow automation	Mid-market entities	AI features embedded natively in ERP modules	SOC 1 and SOC 2 reports; ERP-level segregation of duties
MindBridge	Audit risk analytics	Unsupervised machine learning; ensemble anomaly detection on full ledgers	Mid-sized and large entities; audit firms	Standalone audit analytics platform with CSV and ERP ingestion	Per-transaction risk scores with control-point explanations; SOC 2
CaseWare	Audit data analysis	Statistical sampling and scripted analytics; machine learning add-ins	Mid-sized and large entities; audit firms	Desktop and cloud-based analysis tool used during fieldwork	Reproducible analysis scripts with full documentation trail
Inflo	Audit analytics and predictive risk	Machine learning; predictive analytics on transactional data	Large entities and Big Four engagements	Cloud platform with direct ERP and general ledger connectors	Embedded within structured audit methodology and review workflow
TeamMate+ Audit	Audit management and risk scoring	Machine learning for engagement risk assessment	Large entities and internal audit functions	Integrated audit management suite (planning, fieldwork, reporting)	Enterprise audit governance controls and approval hierarchies
GL.ai (PwC)	General-ledger anomaly detection	Deep neural networks for anomaly identification on full GL populations	Large entities audited by PwC	Proprietary platform deployed inside PwC audit engagements	Vendor-stated explainability of flagged items; firm-internal governance
H2O AI Cloud	AutoML and AI platform	Deep learning; automated machine learning; MLOps tooling	Enterprise entities and large audit firms	Cloud and on-premises platform with API and notebook access	Driverless AI explainability layer; model monitoring and lifecycle controls

Note: Information was compiled from vendor documentation publicly available at the time of analysis (2024–2025). Trustworthiness and governance attributes reflect features explicitly disclosed by vendors and do not constitute an independent assurance or certification assessment.

The first area addressed is the automation of accounting activities. This involves the implementation of artificial intelligence to simplify and accelerate accounting processes that are typically manual and repetitive. For example, AI systems are able to read and interpret invoices and receipts and automatically generate accounting entries, thereby increasing efficiency and reducing processing time (Lee & Tajudeen, 2020; Jędrzejka, 2019; Dext, 2023). The second area concerns the use of AI in financial data analysis. Artificial intelligence can be applied to explore and better understand financial information, supporting more informed decision-making. It is capable of identifying patterns, trends, and insights within financial data that would be difficult to detect without computational support (Moll & Yigitbasioglu, 2019; Domo, 2023; IBM, 2023). The third area focuses on predictive accounting, which involves the use of AI to forecast future events or identify potential financial issues. By analysing current financial and economic data, AI can generate accurate forecasts regarding future developments. This supports strategic planning, trend identification, and the evaluation of financial position (Hasan, 2022; H2O.ai, 2023a).

Following the analysis of the identified software solutions, it becomes clear that each provider attempts to deliver an automated solution, often including predictive capabilities to support efficient strategic decisions. Although an attempt was made to classify these solutions, strict categorisation proved difficult, as most platforms integrate multiple functionalities.

Botkeeper

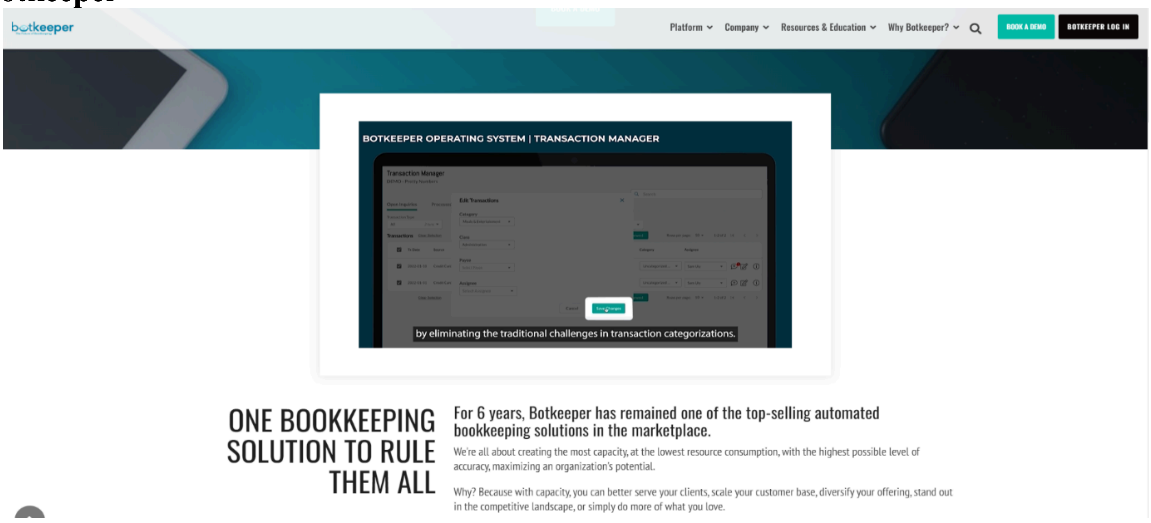

Figure 2. Botkeeper

This software uses machine learning and automated workflow tools, such as robotic process automation, to streamline accounting processes, including payment reconciliations, invoice entry, cash transaction classification, billing, POS reconciliation, reporting, and cash flow management. The platform is primarily configured for accounting practices in the United States (Botkeeper, 2023; Chukwuani et al., 2020).

Dext

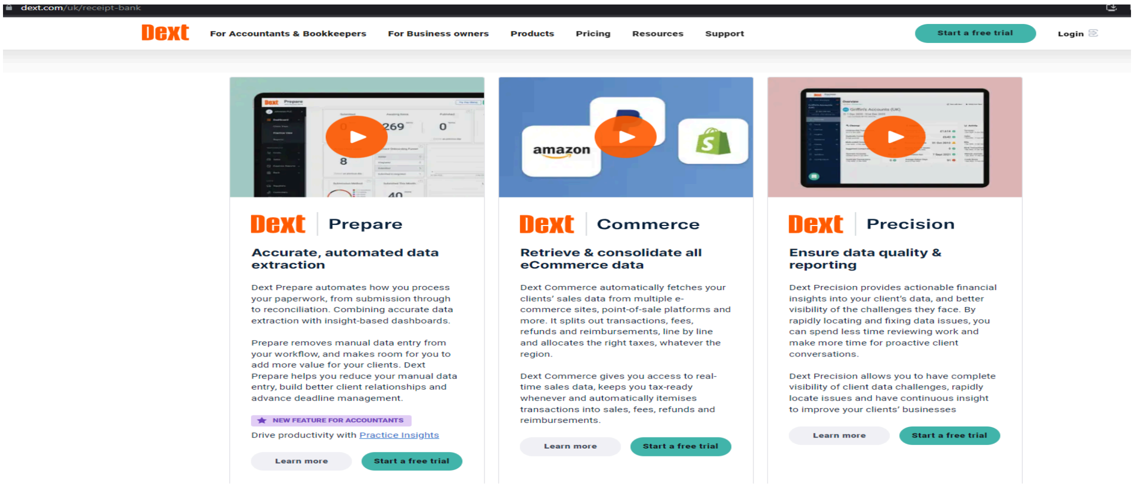

Figure 3. Dext

Dext consists of three AI-integrated tools: Dext Prepare, which scans documents (invoices, receipts, bank statements) and extracts relevant data for import into accounting software; Dext Commerce, which aggregates sales data from multiple platforms for real-time visibility; and Dext Precision, which verifies data and ensures accurate financial reporting (Dext, 2023).

IBM Business Analytics Enterprise

IBM Business Analytics Enterprise is an advanced analytics platform that allows organisations to explore and customise analytical content without programming knowledge. The solution integrates predictive analytics, reporting, data analysis, and data integration. Using extracted insights, businesses can adjust plans, budgets, and forecasts in real time. The platform supports both historical and real-time data analysis, while offering data-cleaning, integration, visualisation, and forecasting capabilities (IBM, 2023; Loebbecke & Picot, 2015).

Domo

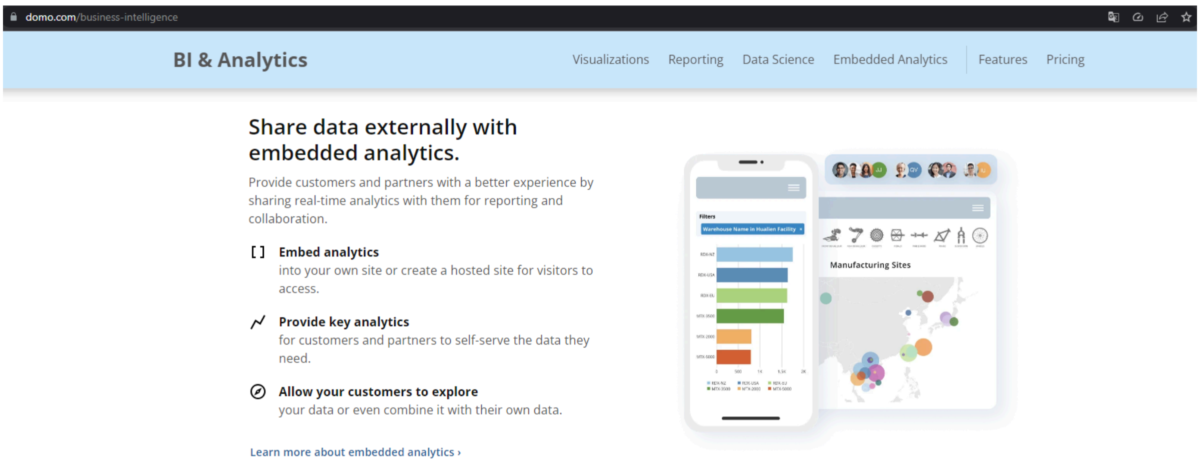

Figure 4. Domo

Domo is a business intelligence platform that makes data more accessible and actionable. Through dashboards, alerts, visualisations, and real-time reporting, users can extract valuable insights. The platform supports data exploration and replaces static spreadsheets with real-time dashboards that can be securely shared. Domo uses AI and machine learning to predict outcomes and analyse data trends (Domo, 2023; Moll & Yigitbasioglu, 2019).

Sage Intacct

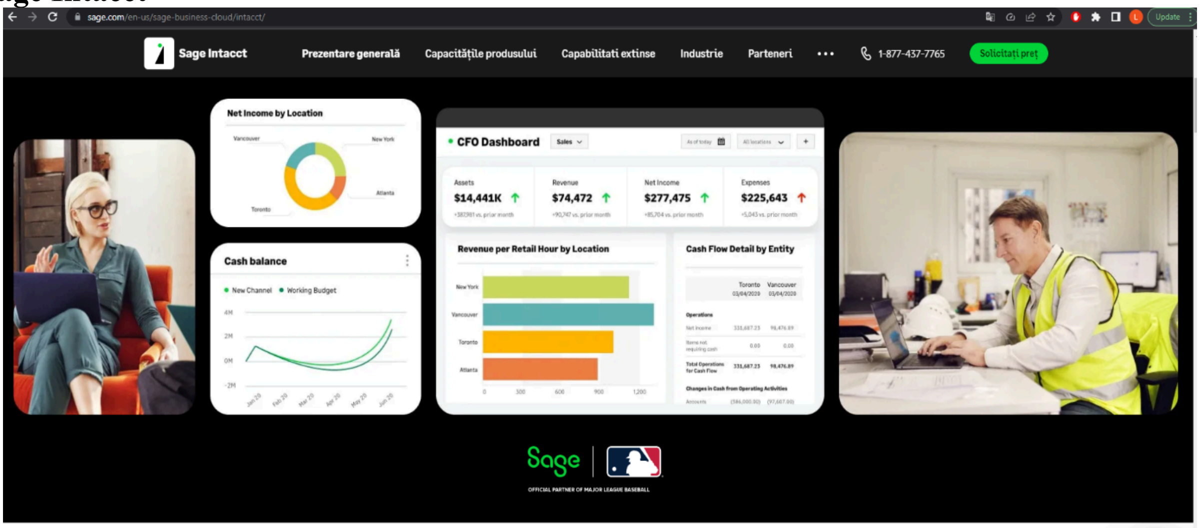

Figure 5. Sage Intacct

Sage Intacct provides cloud-based financial solutions that integrate with existing tools and automate accounting processes. The platform includes core accounting functions such as receivables, payables, billing, cash management, general ledger, procurement, and order management, as well as management reporting and real-time predictive analytics. It allows rapid creation of dashboards and offers both prebuilt and customisable visualisations (Sage, 2023; Lee & Tajudeen, 2020).

6.2. Examples of Artificial Intelligence Integration in Auditing

In the auditing field, the use of artificial intelligence technologies and specialised software plays an important role in improving efficiency and accuracy. These solutions support financial data analysis, audit-risk identification, audit-testing procedures, and the evaluation of accounting information quality (Fedyk et al., 2022; Noordin et al., 2022).

The first category, financial-data analysis and audit-risk identification, involves the use of AI to analyse financial data and detect potential issues or errors. These tools apply predictive analytics and machine learning techniques to identify suspicious behaviour, anomalies, and fraud risks (Fedyk et al., 2022; MindBridge, 2023).

The second category, audit-procedure testing, uses AI to automate and simplify audit-testing processes. These tools enhance efficiency, support risk identification, and optimise audit workflows, reducing both time and cost (Moffitt et al., 2018; CaseWare, 2023).

The third category, evaluation of accounting information quality, focuses on using AI to assess and improve the quality of financial reporting. These systems analyse data to verify consistency and accuracy, identifying potential issues and supporting informed decision-making (Noordin et al., 2022; Kommunuri, 2022).

Although each software solution can be associated with one of these categories, most cannot be strictly limited to a single category due to their integrated functionalities. Therefore, each solution is discussed individually.

MindBridge

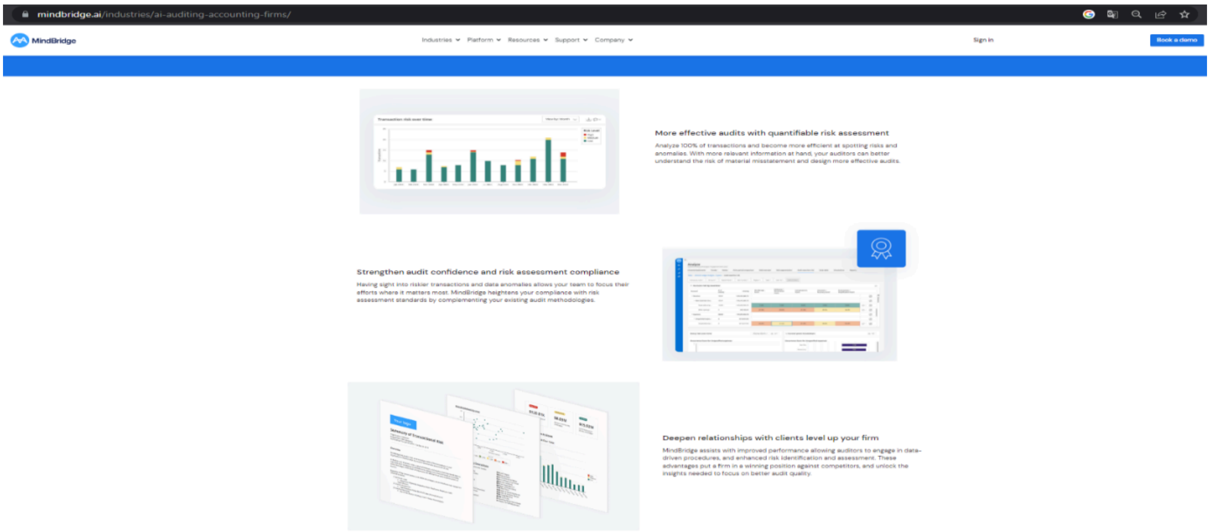

Figure 6. MindBridge

MindBridge provides AI-driven solutions to enhance audit efficiency through data science. The software enables auditors to analyse all transactions and identify risks and anomalies in financial data. It supports a more comprehensive understanding of material-misstatement risk and contributes to improved audit quality. The system uses over 40 control points and applies Ensemble AI to detect patterns and relationships across transactions, offering deeper insight into financial data (MindBridge, 2023; Fedyk et al., 2022).

CaseWare IDEA

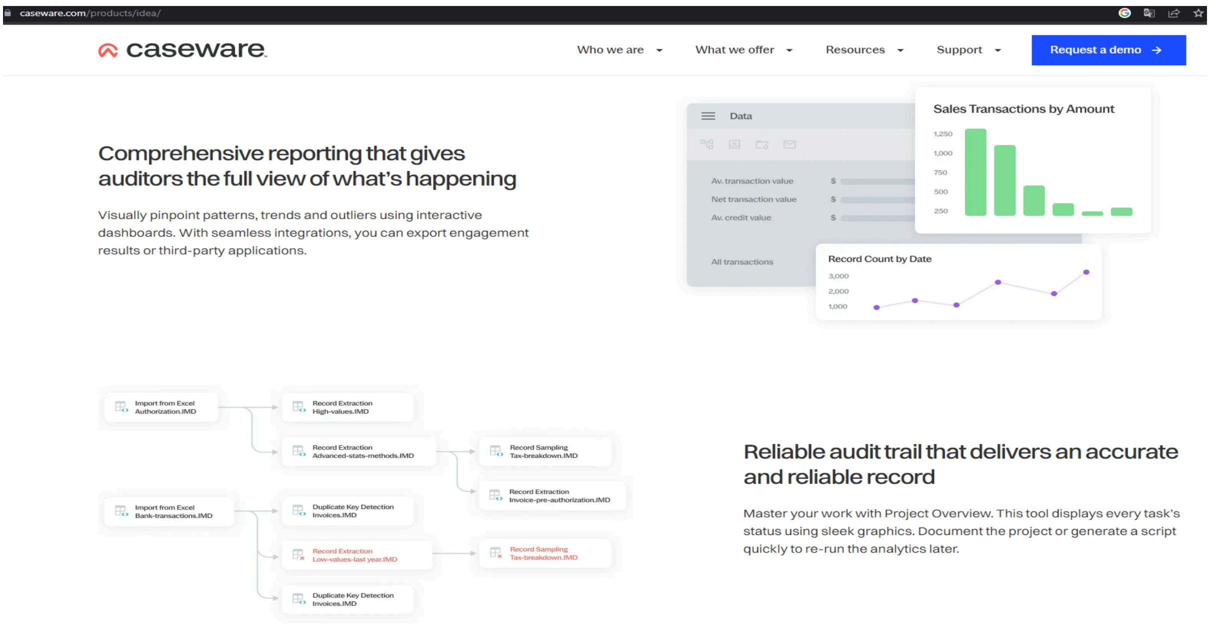

Figure 7. CaseWare IDEA

CaseWare is a platform that automates data analysis, increases productivity, and reduces error risk. It contributes to risk management by ensuring data security and confidentiality and provides clear risk visualisation through risk-based sampling. IDEA enables rapid analysis of large datasets, eliminating manual work and ensuring data integrity by restricting access to source data (CaseWare, 2023; Moffitt et al., 2018).

Inflo

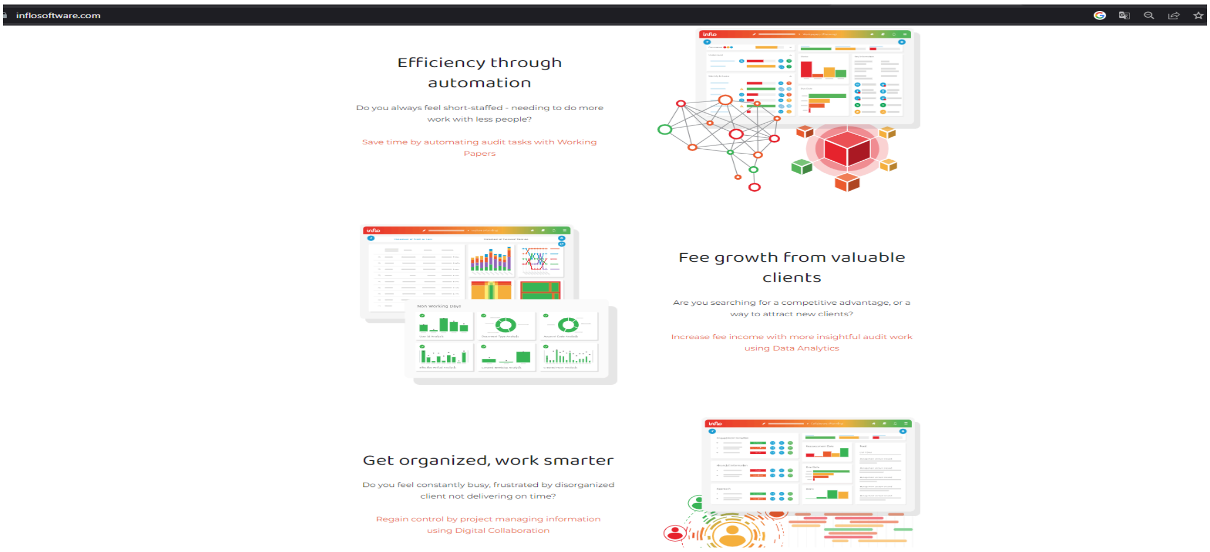

Figure 8. Inflo

Inflo is an audit platform designed for professionals, aiming to optimise and enhance the audit process. The platform integrates several core functionalities, including:

- **Working Papers**: automates audit tasks and supports a data-driven audit approach, improving efficiency and quality;
- **Data Analytics**: enables analysis of 100% of client transactions, improving audit depth and providing competitive advantage;
- **Digital Collaboration**: facilitates project and information management, improving client interaction;
- **Quality Management**: ensures compliance with current audit standards and best practices, strengthening confidence in audit quality (Inflo platform; Kokina & Davenport, 2017).

Overall, these examples highlight the transition from traditional audit approaches based on sampling towards full-population data analysis, supported by artificial intelligence technologies.

KPMG Clara

KPMG Clara is an intelligent and intuitive audit platform, supported by Microsoft Azure, representing one of the major technological innovations in the auditing industry. As an integrated, scalable, and cloud-based platform, it enhances audit methodology through a data-driven workflow. The platform incorporates emerging technologies, advanced data science capabilities, audit automation, and data visualisation tools. KPMG Clara provides clients with continuous (24/7) access to the status of an audit within a single interface, enabling more focused and relevant discussions regarding findings, risks, and insights (KPMG, 2023; Kokina & Davenport, 2017).

KPMG's audit practice benefits from strategic alliances with leading technology companies such as Microsoft, ensuring that its technological capabilities remain highly competitive. These developments are part of a broader transformation of the audit function, aimed at leveraging advanced technologies to deliver higher-quality outcomes (KPMG, 2023; Fedyk et al., 2022).

TeamMate+ Audit

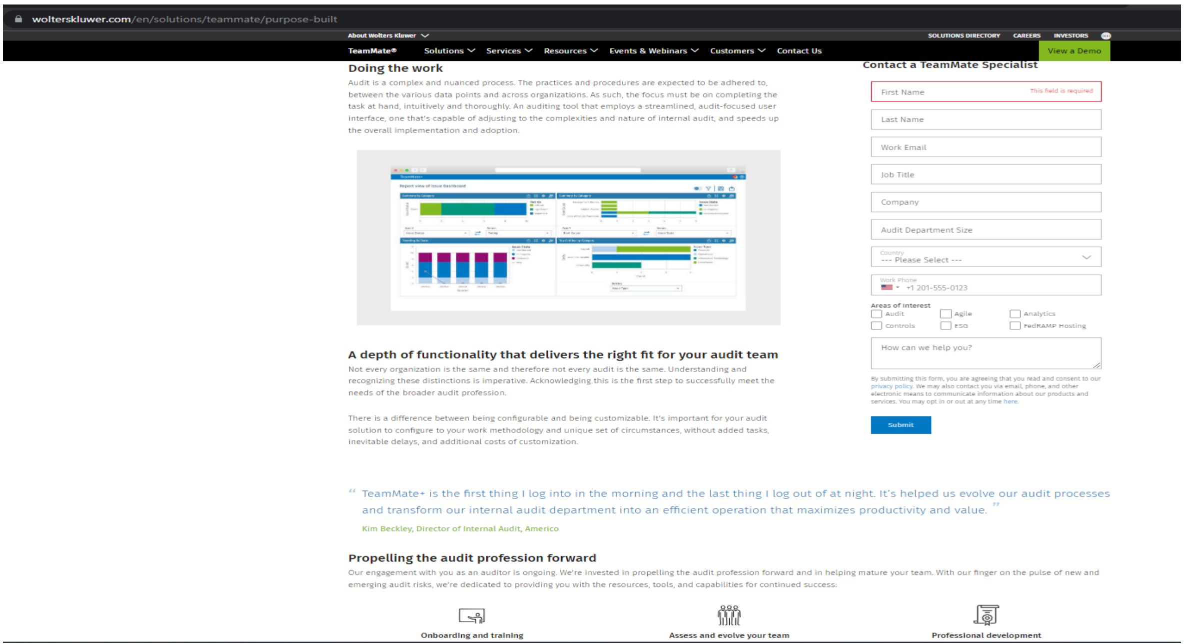

Figure 9. TeamMate+ Audit

Audit tools such as TeamMate+ provide tailored functionalities designed to facilitate the audit process and accelerate implementation. According to the developers, such tools must be configurable, not merely customisable, in order to align with the working methods and specific circumstances of each organisation without introducing additional burdens. TeamMate+ supports and promotes the audit profession by offering resources, tools, and opportunities for continuous professional development in areas such as risk management, data analytics, and Agile methodologies (Wolters Kluwer, 2023; Moffitt et al., 2018).

GL.ai by PwC

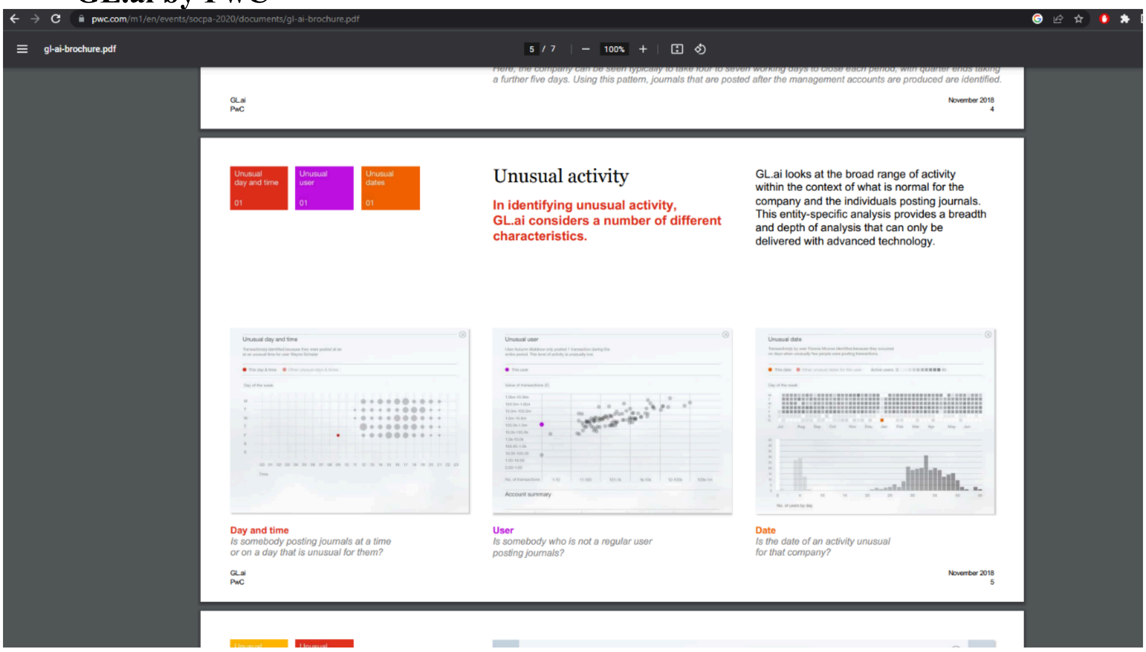

Figure 10. GL.ai

PwC has made investments in artificial intelligence for auditing and collaborated with a Silicon Valley company to develop an innovative solution known as GL.ai. This tool uses artificial intelligence and machine learning to analyse billions of data points rapidly and to detect anomalies within a company's general ledger. In 2017, GL.ai was recognised as "Audit Innovation of the Year," reflecting its impact on the audit process (PwC, 2023b; Fedyk et al., 2022).

GL.ai has been successfully tested in over 20 audits conducted across 12 countries, demonstrating its capacity to accelerate audit processes. By generating data-driven insights that enhance efficiency, the system focuses attention on areas of genuine risk. Its ability to process entire datasets eliminates the limitations associated with traditional sampling techniques (PwC, 2023b; Noordin et al., 2022).

In addition, PwC continues to expand its Audit.ai platform by developing new modules aimed at transforming audit practices. These modules enhance service quality, efficiency, and client interaction, allowing auditors to allocate more time to strategic thinking, communication, and relationship building. The algorithms, trained using PwC's global expertise, identify unusual transactions with high precision by analysing journal entries and user behaviour patterns (PwC, 2023b; Tiron-Tudor & Deliu, 2022).

Unusual account activity may arise from rare combinations or atypical usage patterns over time. GL.ai reconstructs the timing of period-end entries and identifies delays or irregularities depending on the reporting cycle. By integrating multiple analytical features, the system provides a granular understanding of financial data, enabling auditors to detect high-risk entries and potential manipulation more effectively (PwC, 2023b).

H2O AI Cloud

Figure 11. H2O AI Cloud

H2O AI Cloud is a platform designed to accelerate and scale artificial intelligence outcomes with reliability and robustness. It addresses organisational challenges such as inefficient operations, risk management issues, customer volatility, and research limitations by providing advanced

AI-driven solutions. The platform relies on high-performance machine learning to enable organisations to build predictive models and extract insights from data efficiently (H2O.ai, 2023a). The key components and services of H2O AI Cloud include:

- **H2O-3**: an open-source distributed machine learning service;
- **H2O Document AI**: a solution for intelligent data extraction;
- **H2O Hydrogen Torch**: a no-code deep-learning platform;
- **H2O Wave**: a low-code AI application development framework;
- **H2O AI Feature Store**: a service for managing data features;
- **H2O MLOps**: a service for model deployment, monitoring, and management;
- **H2O AI AppStore**: a marketplace for AI applications across industries.

The platform supports multiple sectors, including financial services, government, healthcare, insurance, manufacturing, marketing, retail, and telecommunications (H2O.ai, 2023a).

H2O Document AI is an advanced solution that combines Intelligent Character Recognition (ICR) and natural-language processing to extract information from forms and unstructured text. It converts documents into structured data, facilitating data collection from diverse sources and supporting various business functions. Through seamless integration with existing applications, the solution provides automated data labelling, accurate extraction of key information, and an intuitive user interface. Through REST APIs and integration with H2O MLOps and H2O Wave, it enables rapid development and deployment of AI models, ensuring efficient and scalable process management (H2O.ai, 2023b).

7. Conclusion, Limitations and Future Research Directions

The findings of this study can be summarised against the three research questions formulated in Section 1. In response to RQ1, the bibliometric analysis of 729 Web of Science articles indexed after 2015 indicates that the field is structured around six dominant terms (artificial intelligence, deep learning, machine learning, performance, classification and model), with conceptual clusters that link AI techniques to predictive performance and to financial classification tasks rather than to broader assurance themes. Methodological orientations remain concentrated on technique-driven studies and case descriptions, while integrative reviews that bridge bibliometric mapping with applied evaluation are still scarce.

In response to RQ2, the exploratory comparison of ten AI-based solutions identified three functional categories: data capture and transactional processing (Botkeeper, Dext), business intelligence and embedded ERP analytics (Domo, Sage Intacct), and audit-oriented analytics and predictive systems (MindBridge, CaseWare IDEA, Inflo, TeamMate+ Audit, GL.ai, H2O AI Cloud). Architectural choices follow a layered pattern (data, feature, model, decision-support and governance layers), and the integration mode varies systematically with entity size: small and medium-sized entities consume embedded AI features as a standardised service, whereas large entities and Big Four firms deploy specialised platforms supported by internal data science and governance functions.

In response to RQ3, the analysis treats trustworthiness as a constitutive feature of AI systems rather than as an absence of errors. Vendor disclosures show heterogeneous coverage of explainability, audit trails and governance controls, with stronger documentation in audit-oriented platforms (MindBridge, GL.ai, H2O AI Cloud) than in transactional tools. The regulatory environment, in particular the EU AI Act, ISO/IEC 42001 and the NIST AI RMF, will shape adoption through different practical pathways for SMEs (provider-mediated compliance) and for large entities (internal governance and validation). These asymmetries should be reflected in future professional standards for AI-supported accounting and auditing.

From the perspective of contributions, the study delivers four targeted outputs that distinguish it from previous reviews. First, it provides a structured bibliometric mapping of the post-2015 literature on AI in accounting and auditing, anchored in a transparent four-stage screening protocol. Second, it develops a comparative profile of ten AI-based solutions along functional, architectural, entity-size and trustworthiness dimensions (Table 1), bridging the gap between technological description and professional use. Third, it integrates the trustworthiness debate (HLEG, 2019; ISO, 2023; NIST, 2023; European Parliament, 2024) into the accounting and auditing discussion, treating it as a property to be designed and audited. Fourth, it formulates an entity-size differentiation of AI adoption that connects SME and large-entity profiles to distinct compliance pathways.

The selection of an AI-based solution, whether developed internally or acquired externally, must consider the specific characteristics and needs of the organisation, as well as the available resources and expertise. Regardless of the chosen approach, the implementation of advanced intelligent systems can generate benefits in terms of operational efficiency, productivity, and cost reduction, thereby contributing to long-term competitiveness and organisational success (Gambhir & Bhattacharjee, 2021; Salawu & Moloi, 2020).

This study examined the role of artificial intelligence in accounting and auditing by integrating bibliometric evidence with an exploratory analysis of AI-based solutions, providing a structured perspective on how these technologies are embedded in financial processes and contribute to their transformation. The research focused on identifying the main directions within the literature, systematising core AI concepts and technologies, examining current applications, and assessing their impact on financial processes and professional roles.

The findings indicate that the adoption of artificial intelligence contributes to increased efficiency and productivity in accounting and auditing processes, while also generating new requirements in terms of professional skills and continuous training. The integration of AI systems into financial workflows is associated with a gradual transformation of professional roles, requiring stronger analytical capabilities and the ability to interpret and supervise automated processes. In this context, aspects such as human–AI interaction and user acceptance may influence the effective implementation of these technologies, representing areas that require further investigation.

The findings suggest that artificial intelligence has the capacity to streamline and optimise accounting and audit processes through automation, large-scale data analysis, and enhanced decision support. AI-based solutions may be implemented within organisations either through internally developed systems tailored to specific operational needs or through externally acquired platforms that provide integrated functionalities across financial processes.

The implementation of such solutions brings a series of benefits for companies open to innovation, including improved execution time for accounting and audit processes, the reduction of errors and fraud, lower operational costs, and the possibility to reallocate human effort towards activities requiring advanced expertise and analytical judgement. At the same time, these developments support the strengthening and scaling of organisational performance in increasingly competitive environments.

Alongside these benefits, several risks and challenges must be considered, including data security and confidentiality risks, dependence on technological systems, and the need for continuous adaptation of professional competencies. The potential impact on employment should be understood primarily as a transformation of roles rather than a complete reduction, with increasing demand for advanced skills in data analysis, supervision, and decision-making. In addition, the implementation of AI systems involves additional costs related to IT expertise, cybersecurity, and system maintenance.

The analysis of AI applications indicates that accounting processes are increasingly supported by automation, data analytics, and predictive functionalities, which enable more efficient data processing and improved decision support. Similarly, in auditing, AI technologies facilitate risk identification, audit testing, and the evaluation of financial information quality through the analysis of entire data populations, enhancing both efficiency and accuracy.

Overall, the adoption of artificial intelligence in accounting and auditing generates benefits but also requires a balanced approach in which technological capabilities are aligned with organisational needs and supported by appropriate governance and training mechanisms.

This study has several limitations. First, the analysis is based on secondary data and does not include empirical validation of the performance of the analysed AI systems. Second, the selection of software solutions, although structured, may reflect a degree of selection bias towards widely used or well-documented platforms. Third, the study adopts a general perspective, without addressing in detail sector-specific or organisational differences.

Beyond these general limitations, three more specific constraints should be acknowledged. First, the bibliometric corpus is restricted to Web of Science records and to English-language articles, which excludes regional accounting journals and grey literature where SME-related evidence is often reported. Second, the comparative profile presented in Table 1 relies on vendor documentation publicly available at the time of analysis (2024–2025); features and trustworthiness disclosures may evolve as the EU AI Act and ISO/IEC 42001 enter operational use. Third, the study does not include primary empirical evidence on implementation outcomes: performance, error rates, user acceptance and audit-effectiveness measures remain to be tested in subsequent fieldwork.

Future research could address these limitations through three complementary directions. First, longitudinal bibliometric updates that incorporate Scopus and regional databases would help detect emerging clusters around trustworthy and explainable AI in accounting. Second, case-based and survey-based studies focused on SMEs would clarify how provider-mediated AI services are governed in entities without dedicated data-science teams. Third, audit-effectiveness studies are needed to evaluate whether ML-based anomaly detection (such as that implemented in MindBridge or GL.ai) improves the detection of misstatements and fraud relative to traditional analytical procedures and under what trustworthiness conditions these improvements hold.

Future research could extend this work by developing empirical analyses of AI implementation in accounting and auditing environments, including performance evaluation, cost–benefit analysis, and user adoption. Further studies may also explore the integration of advanced computational models and their implications for financial decision-making and regulatory frameworks.

Acknowledgement

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