Human versus Machine

Accounting, Auditing and Education in the Era of Artificial Intelligence

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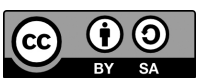

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Preface

The latest artificial intelligence (AI) developments have started reshaping the world we know. Accounting and auditing professionals' future tasks and skills have also become subject to many changes (ICAEW, 2018; Leitner-Hanetseder et al., 2021). As Hassan (2022, p. 444) emphasises, "AI, according to most definitions, is hardware and software that can learn, reason, adapt, analyse, make judgments, and execute complicated and judgment-based activities in the same way as the human brain can." The new AI-based accounting tools and software enhance their outcomes through learning and become closer to humans' cognitive abilities in performing specific tasks (Lehner et al., 2022; Munoko et al., 2020). Thus, the accountancy profession is undergoing a kind of revolution reflected in automating monotonous and repetitive operations (Kommunuri, 2022), reducing the possibility of fraud and discrepancies in accounting data (Chukwuani and Egiyi, 2020) and improving the quality of managerial accounting (Chen et al., 2021) due to provision of real-time data analytics to boost corporate performance (Appelbaum et al., 2017).

However, the growing importance of AI-based accounting tools and software caused accounting and auditing professionals, researchers and educators to raise challenging questions on whether it would be possible to have AI solutions that mirror human intelligence in the accounting domain (Weber, 2023) or whether it would be possible to perform human-machine hybrid work (Mollick, 2022) particularly when the autonomy of AI-based solutions (Rieder et al., 2020) may shift decision-making from humans to technical systems (Heyder et al., 2023). These problems drive another issue (Heyder et al., 2023): How can we understand and explain the ethical management of human-AI interaction? Zhang et al. (2023) address some ethical concerns related to applying AI systems in managerial accounting, indicating that risks of de-professionalisation, data breaches, and isolation among accountants may occur. Other ethical implications may also appear, such as whether AI technologies will consider justice and fairness with regard to vulnerable groups (Villegas-Galaviz and Martin, 2022) or whether too much trust in AI will not get rid of managerial accountants from professional judgement (Sutton et al., 2023). Considering the latest AI developments and other burning issues, such as climate change and increasing societal demands for business transparency and accountability, Carnegie et al. (2020) attempted to redefine accounting, arguing that the conventional understanding of accounting inaccurately portrays the profession, as it dates back to when it was still in its early stages of professionalisation and fails to acknowledge the progress

made in scholarship and practice. In a given context, they put forward a novel potential definition: *"Accounting is a technical, social, and moral practice concerned with the sustainable utilization of resources and proper accountability to stakeholders to enable the flourishing of organisations, people and nature*." (Carnegie et al., 2020, p. 69). It should be noted that moving beyond an obsolete, restricted and technical way of thinking about accounting may re-image the perception of this field and instil interdisciplinary cooperation with experts in other disciplines, generating a synergistic value for the future of the accounting profession.

This monograph addresses the broad aspects of human-AI interaction in accounting, auditing, and reporting practices, as well as the effects of using AI applications in the area of education. It includes eight chapters written by authors from various countries, including Croatia, Italy, Lithuania, Moldova, Poland, Romania, Slovenia and Spain. The international context of the book, reference to the latest literature on AI applications in business accounting, and presented research study can make this work valuable and interesting for those interested in the opportunities and threats that AI may bring into the professional lives of many.

The rapidly approaching fifth industrial revolution environment is causing most business professions to undergo profound change, and the accountancy profession is no exception. In the first chapter, **Mirjana Hladika, Petra Halar,** and **Dubravka Kopun** provide a comparative review of the literature and present a critical reflection on the state and perspectives of the accountancy profession and the required competencies of accountants in the age of the fifth industrial revolution, as well as indicate the scope of accounting operations and processes that AI could take over in the (near) future.

The second chapter, written by **Paweł Miszczuk and Piotr Bednarek**, delves into integrating AI within auditing, encompassing external and internal processes. The authors emphasise that auditing can particularly use data analytics and AI applications since analyses of vast volumes of structured and unstructured data to gain insight into companies' financial and non-financial performance have become much more challenging recently. By investigating recent research studies, the authors try to find out how and to what extent AI technology (i.e. machine learning (ML), deep learning (DL), natural language processing (NLP), and robotic process automation (RPA)) can be applied in external and internal audit processes.

The third chapter investigates the issues regarding the impact of AI applications on auditing by reviewing research papers published mainly between 2021 and 2023. **Piotr Bednarek** and **Paweł Miszczuk** discuss the major AI applications in auditing and explore the benefits of AI use in increasing auditing work's effectiveness, efficiency, and quality. They further address the significant challenges of the auditing profession due to AI investments by pointing out the problem of human auditors' displacement by AI solutions, potential biases in judgment due to AI use, the importance of auditors' judgment in automated processes, and the challenges of integrating emerging technologies into professional practice and education, i.e. the need for continuous acquiring new skills and updating curriculums.

In the fourth chapter, **Assunta Di Vaio, Anum Zaffar, and Daniel Balsalobre-Lorente** discuss the relationship between AI and the attestation of sustainability reports as the firms face institutional pressures exerted by regulatory bodies, society, corporate governance codes, standard-setting bodies and industry norms to present a clear picture of their sustainable performance without harming nature. The authors refer to such AI tools as ChatGPT, ChatReport, Natural Language Processing (NLP), Machine Learning (ML) and Latent Dirichlet Allocation (LDA) and discuss their opportunities for the assurance process of sustainability reports.

The fifth chapter examines what internal audit will look like in the future, how many internal audit tasks will be taken over by AI in the next ten years, and whether an internal audit profession will still exist then or an AI solution will replace it. The author of this chapter – **Iztok Kolar** – collected data through a questionnaire sent to all internal auditors at the Slovenian Institute of Auditing and all members of the Slovenian IIA Chapter and gathered 91 completed and usable fillings. The questionnaire was active between 25 February 2024 and 15 March 2024. As was emphasised in the study, the future of internal audit and the internal audit profession is a hot topic of research at the moment since, to some extent, internal auditing is losing attention and relevance in its operating environment, and stakeholders currently notice less and less added value in internal auditors' job. Therefore, there are claims that the internal audit profession is at a critical juncture (Lenz and Jeppesen, 2022).

The next chapter highlights how AI can support and optimise integrated reporting processes, providing a detailed perspective on its potential to transform how organisations manage and communicate their financial and non-financial performance. The research study developed by **Ana-Carolina Cojocaru, Svetlana Mihăilă, Veronica Grosu**, and **Ludmila Frumusachi** addresses how AI technologies can be understood and applied to collect, analyse, and disclose important data about company outcomes. The authors applied various research methods, including bibliometric analysis, comparison of previous studies, and the induction and deduction of significant ideas based on literature findings.

Rapid technological progress and the introduction of diverse AI tools have changed several domains, such as accounting business and education. AI is transforming conventional methods, enhancing data management and increasing the precision and effectiveness of financial decision-making. In addition to changing business procedures, AI also influences changes in teaching and learning strategies. In the seventh chapter, **Rasa Subačienė** and **Daiva Tamulevičienė** investigate recent research studies on AI in accounting business and education included in the Web of Science database. They used *VOSviewer* and *RAYYAN* tools to analyse the literature and applied traditional information systematisation and generalisation methods.

The importance of AI in the teaching and learning process is becoming indisputable. Universities should support students and academics in using AI tools. The last chapter analyses regulations concerning the use of generative AI in teaching and learning at selected Polish universities. **Angelika Kaczmarczyk** speaks in

a discussion on the changes that are taking place in universities concerning the use of AI tools. The author emphasises the need to raise awareness about the opportunities, potential benefits, and threats of using these technologies and highlights the role of openness and critical thinking in applying generative AI in higher education.

In conclusion, the monograph offers insight into the results of the latest research studies on the application of AI tools in accounting and education. It presents various perspectives and indicates the possibilities of using AI in accounting practices, internal and external audits, and reporting processes. With this focus and scope, this publication may be intriguing and absorbing for accounting scholars, doctoral and master's students, and business practitioners. The book can also be used as supplementary material for accounting, auditing and reporting courses at the graduate and postgraduate levels.

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Chapter 1

The Impact of Artificial Intelligence on the Future of the Accounting Profession: A Literature Review

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Contemporary era and companies' business environment are faced with the next (fourth and/or fifth) industrial revolution, whose main characteristics are socio-technologically driven innovations brought by technologies and concepts of value chain organisations (Barata and Kayser, 2023; Hermann et al., 2015). In other words, humans and machines are envisioned to work together in a virtual reality (ATOSS, n.d. b; Dai and Vasarhelyi, 2016). Terms like digital technologies, digitalisation, digital business transformation, cultural change, agility, and similar have become commonplace. Among all other primary and secondary digital technologies, artificial intelligence (AI) represents a breakthrough or a disruptor technology that

has the ability to surpass all other technological solutions and bring enormous enhancements to companies' business operations and their "front-" and "back--office" business functions. The digital transformation of businesses is the process of implementing technological solutions in all business processes in order for the company to remain competitive. Parallel to the digital transformation of businesses, a cultural change is taking place (Sabuncu, 2022). For the process of digital business transformation and digitalisation to be successful, the key lies in humans and their willingness to accept changes, learn and master new skills in order to fit into the digital environment as quickly and successfully as possible and perform their tasks efficiently. Accountants are a very important link in the whole process, as accounting is a core function of the company whose role is crucial to the company's success. Accordingly, changes in the business environment, the digitalisation of businesses and the implementation of digital technologies require accountants to acquire new knowledge, skills and abilities (Cordos and Tiron-Tudor, 2023a; Grosu et al., 2023; Kroon et al., 2021; Yigitbasiouglu et al., 2023). In a digitalised world, the success of accountants (and, accordingly, companies) depends on the effective combination of the use of appropriate technology and a set of right skills. As accountants face changes in their work, it is inevitable that they will need to expand and improve their knowledge, skills and abilities to meet the needs of their clients (Secinaro et al., 2021) and to remain relevant in this increasingly dynamic environment.

Therefore, this chapter seeks to provide answers to the following research questions:

RQ1: What are the key characteristics of companies' business environment in the era of the existing fourth and the upcoming fifth industrial revolution, driven by AI, and how do they affect currently, and will affect in the future, the overall accounting profession, accounting tasks performance and accountants' competencies?

RQ2: Which accounting tasks can and cannot be replaced by AI in the era of the fourth and fifth industrial revolutions?

RQ3: What are the key knowledge, skills and abilities of accountants needed for performing their tasks in the era of the fourth and fifth industrial revolutions?

These research questions lead to the following objectives of the chapter: (1) to identify the key characteristics of companies' business environment in the era of the fourth and fifth industrial revolutions and define their impact on the accounting profession, (2) to investigate which accounting tasks can and cannot be automated, and (3) to identify the new competencies of accountants required to successfully perform accounting tasks in the digital era.

In order to achieve the defined objectives of the research, the authors' desk searched relevant databases, primarily ProQuest, Scopus and Web of Science, Google Scholar search engine, as well as other publicly available secondary sources through the Google search engine to obtain relevant scientific and professional literature

that satisfied predefined criteria. These predefined criteria included the following keywords: "accounting and artificial intelligence", "accounting profession and artificial intelligence", "accountants' competencies and artificial intelligence". Therefore, the authors selected, for critical and comparative review, scientific and supportive professional literature that best suited the research topic and research objectives, for which full text was available in English. Selected literature was analysed by using scientific methods of analysis, synthesis, description, classification, and comparison.

In terms of structure, the chapter begins with section 1.1, which presents the state and perspectives of companies' business environment in the era of the fourth and fifth industrial revolutions driven by AI. This is followed by section 1.2, which analyses the impact of the use of AI on the accounting profession. Section 1.3 discusses accounting tasks that can be automated through the use of new digital technologies, primarily AI, whereas section 1.4 identifies areas in which AI will not be applied. This is followed by section 1.5, which provides a comprehensive insight into the competencies of accountants in the future. The whole chapter ends with concluding remarks, implications, and directions for future research on this emerging topic in the field of accounting, as well as with stating the limitations of the research.

1.1. Companies' Business Activities' Disruptions in the Environment of the Fourth and Fifth Industrial Revolutions

Currently, the corporate world is in the era of the fourth industrial revolution, which can be described as a disruption of companies' business activities performance and transformation of their overall business models, driven by digital technologies that allow creating greater added value in all parts of the value chain and for all involved parties, horizontally and vertically, by continuously exchanging information in a real-time. Originated in the industry and manufacturing, this next revolution has spread rapidly to all other economic sectors and professions and changed their traditional postulates and ways of working. Hermann et al. (2015, p. 11) define Industry 4.0 as an overall paradigm that gathers technologies and concepts of value chain organisations. Four key components of the fourth industrial revolution are cyber-physical systems, the Internet of things, the Internet of services and smart factory, while its core principles are interoperability, virtualisation, decentralisation, real-time capability, service orientation and modularity (Hermann et al., 2015). Digital technologies, as primary drivers and enablers of companies' digital business transformation, include, among others, mobile technologies, cloud computing, big data analytics, sensors, robots, drones, 3D printing, augmented and virtual reality, blockchain technology, nanotechnology, as well as AI. The main purpose of this current industrial revolution is to increase the value chain flexibility "by maximising the transparency of inbound and outbound logistics, manufacturing, marketing, and all other business functions such as accounting, legislation, human resource, etc." (Dai and Vasarhelyi, 2016, p. 1).

To achieve that, data need to be continuously interchanged (collected, transmitted and analysed) inside and outside a company in real-time to enhance decision-making processes, reduce costs, increase and make productivity gains, improve the effectiveness and efficiency of business operations, and capture strategic business value in the end (Dai and Vasarhelyi, 2016; Goering et al., 2018; Onyshchenko et al., 2022; Özcan and Akkaya, 2020). The results are radically transformed company's activities and the ways its business functions work, including accounting. The 'smart' or 'intelligent' company is envisioned, whose main feature is 'organisational agility', which can be defined as the ability to adapt quickly to changes so that the company can survive in a competitive environment by meeting customer demands and expectations promptly (Şen and İrge, 2020).

Furthermore, a new hot topic regarding industrial revolutions is the fifth industrial revolution or Industry 5.0. Regarding that, in both academia and practice, there exist two stances. The first stance is that the fifth industrial revolution is the next industrial revolution that will surpass Industry 4.0, while the second is that Industry 5.0 is just an evolution of the fourth industrial revolution. The agreement on what is more accurate is yet to be achieved. Nevertheless, Industry 5.0 can be defined as a "humanised vision of technological transformations in industry, balancing the current and future needs of the workers and society with the sustainable optimisation of energy consumption, materials processing, and product lifecycles" (Barata and Kayser, 2023, p. 778). According to Barata and Kayser (2023, p. 785), industry 4.0 is more technologically driven, while industry 5.0 is more socio-technically driven, but both are expected to continue their progress side--by-side, revolutionising corporate business. This is in accordance with the statement that Industry 4.0 integrates automation and data exchange in business activities, while Industry 5.0 enables collaboration between humans and machines (ATOSS, n.d. b). The strengths of Industry 4.0 will be even more emphasised by concepts of Industry 5.0 so that companies can be even more agile and future-ready (ATOSS, n.d. b). AI is an instrument that will strengthen the collaboration between humans and machines, with the mission of creating sustainable products and services (ATOSS, n.d. b). "In Industry 5.0, digitalisation is used to answer broader questions regarding environmental, energy, and social challenges. It is hence the integration of the technological determinants that shaped industry 4.0 into the larger context of humanity, spanning the boundaries of the factory floor" (Barata and Kayser, 2023, p. 784).

AI can be defined as "hardware and software that can learn, reason, adapt, analyse, make judgments, and execute complicated and judgment-based activities in the same way as the human brain can" (Hasan, 2022, p. 444). It is, therefore, a self--sustaining and evolving technology because "the more it does, the smarter it becomes, to the point where machines are now teaching other machines and learning on the job" (Hasan, 2022, p. 444). The subsets of AI are machine learning, robotic process automation, artificial neural networks and deep learning (Kommuri, 2022, p. 585). The foundation of AI applications is machine learning models, and today exist three types of AI based on capabilities (IBM Data and AI Team, 2023):

- artificial narrow intelligence or weak AI, which can be trained to perform a single task much faster and better in comparison to a human mind,
- artificial general intelligence or strong AI, which can, based on previously gathered knowledge and skills, accomplish new tasks in different contexts without additional training,
- super AI or artificial superintelligence, for which it is envisioned that it will be able to think, learn, reason, make judgements and possess cognitive abilities surpassing those of human beings.

It is worth noting that, until now, artificial general intelligence and superintelligence are just theoretical concepts (IBM Data and AI Team, 2023). Artificial narrow intelligence can be divided into two categories based on functionalities (IBM Data and AI Team, 2023):

- reactive machine AI, like IBM Deep Blue and The Netflix Recommendation Engine
- limited memory AI, like generative AI, virtual assistants and chatbots, and self-driving cars.

Currently, one of the most popular among three AI types, artificial narrow intelligence's subcategory, generative AI, is related to helping people do their jobs better, so it is envisioned as their 'co-pilots' (Lamarre et al., 2024). The most popular examples of generative AI tools are OpenAI's ChatGPT, Google's Bard, Microsoft's and Nvidia's Megatron, etc. (ISACA, 2023, p. 4).

It is clear that AI will have a very important role in the corporate world in the near future, so companies need to familiarise themselves with the possibilities of this technology application (ATOSS, n.d. b). The adoption and usage of AI technologies in companies' business activities increase effectiveness, efficiency, accuracy, and decision-making capabilities, resulting in improved financial and non-financial reporting (Abdullah and Almaqtari, 2024).

Therefore, the adoption and usage of AI in companies' business activities need to be carefully planned, and proactive and holistic strategies with clear objectives, risk management processes, and internal controls must be developed. Efforts to implement and use AI in companies' business activities should not come at the expense of risk management (ISACA, 2023, p. 4). There are many uncertainties and unknowns regarding this technology, but governance structures need to start preparing and adapting to AI revolutionising their business activities now, as they need to be aware that this technology is already being used within their companies in some form (ISACA, 2023, p. 5), even indirectly and unintentionally. A company's competitive advantage in the modern age "comes from building organisational and technological capabilities to broadly innovate, deploy, and improve solutions at scale – in effect, rewiring the business for distributed digital and artificial intelligence innovation" (Lamarre et al., 2024). Despite unimaginable usefulness and opportunities brought by Industry 4.0 and 5.0 concepts, including the AI revolution, there are also

lots of downsides, primarily in terms of increased cybersecurity, legal issues, ethical issues and all other types of known and unknown risks, as well as the fact that some professions are starting to disappear as certain tasks and jobs are being replaced by innovative technologies. On the other hand, new tasks and jobs are also being developed, such as those related to programming and robot maintenance (ATOSS, n.d. a). There is also a need to develop and adjust governance systems and regulatory requirements related to AI (ISACA, 2023, p. 3).

1.2. Accounting Profession's Disruptions in the Era of Artificial Intelligence

Foundations and principles of Industry 4.0 transformed accounting functions' ways of working and enabled the creation of a mirror (or a virtual) world, which was accelerated in the period of the COVID-19 pandemic (Halar et al., 2023, p. 123). Industry 5.0 will also have a deep transformational influence on the overall accounting profession and accounting functions in companies.

Companies are gaining value by implementing advanced technologies, including AI, into their general and administrative support functions (Edlich et al., 2018). Automation and AI can drastically reshape accounting functions in companies (Plaschke et al., 2018). Automating routine accounting tasks through tech- and especially AI-enabled transformations will deliver substantial impacts for the whole company (Edlich et al., 2018). Some analyses show that around one-third of accounting and finance tasks and activities, like general accounting operations, revenue management, cash disbursement, external reporting, treasury, tax, and the like, can be automated using already available technologies, while other two-thirds require advanced cognitive automation technologies (Edlich et al., 2018; Kommunuri, 2022; Plaschke et al., 2018). Basic technologies include robotic process automation or 'software robotics', business-process management and optical character-recognition tools, among others, while more advanced technologies, for example, are machine--learning algorithms and natural-language tools (Kommunuri, 2022; Plaschke et al., 2018). In the modern era, these basic technologies are mainstream, meaning they are mature and easy to adopt and use in accounting, while advanced ones are not mainstream, as they are still in developing phases but available for implementation and usage in accounting (Plaschke et al., 2018). To capture the full potential of basic and advanced technologies for transforming accounting functions, managers must re-engineer their processes completely (Kommunuri, 2022). AI has wide usability and applicability opportunities in accounting functions. This means that, for example (Plaschke et al., 2018):

- robotic process automation can automate tasks of preparing journal entries,
- machine learning can automate tasks related to reconciling accounting records,
- natural language tools can be used to produce report commentary.

In contrast to offshoring, outsourcing and centralisation as drivers of accounting and finance functions' productivity improvements for decades, in the new industrial revolution and AI era, automation is a new enabler of effectiveness and efficiency gains (Plaschke et al., 2018). To be able to record business transactions without the help of accountants, companies need to invest heavily in their technological infrastructure to adapt it to the requirements of the fourth industrial revolution and become smart (Onyshchenko et al., 2022, p. 173). In the contemporary fourth and rapidly approaching fifth industrial revolution, the discrepancy between an event occurring, its recording and informing about it for decision-making purposes should be minimal, meaning that it should be in real-time. Therefore, terms like continuous accounting, real-time accounting, accounting 4.0, accounting 5.0, etc., have brought wide attention. To cope with disruption challenges in the modern age of AI, digitalisation, and digital transformation, the accounting and financial functions of a company need to plan it strategically and holistically by including people, data, processes and technologies. By automating and transforming their ways of working, scarce resources are saved. Adoption of AI in accounting can increase the accuracy and transparency of financial and non-financial reporting, reduce costs, and improve efficiency and outcomes (Kommunuri, 2022; Wael et al., 2024). On the contrary, AI implementation requires significant infrastructure, software and training investments, high computing power and significant storage capacity (Wael et al., 2024, pp. 5-6). Therefore, a cost-benefit analysis needs to be done to make the right decision regarding the implementation of AI in accounting practices.

In parallel to Industry 4.0, Industry 5.0, AI and other digital technologies, the notion of corporate sustainability or environmental, social and governance (ESG) questions have come to the fore (Burritt and Christ, 2016; Onyshchenko et al., 2022). It is not accidentally, as the fourth industrial revolution has possibilities to improve (Burritt and Christ, 2016, pp. 29-30):

- external environmental accounting: better data quality, reduced opportunities for greenwash and brownwash, less management discretion over measuring and reporting objects, higher credibility of data,
- environmental management accounting: obtainment of previously unobtainable data, raising the quality of data for (environmental) decision-making purposes, better management control, quality data pool for various purposes and stakeholders, piggybacking onto existing manufacturing infrastructure for minimising investment costs.

Digitalisation and transformation of companies in different industries will have impacts on the accounting profession in terms of defining relevant accounting rules and policies for recognition, measurement and disclosure of information about innovative digital technologies as intangible assets (Onyshchenko et al., 2022, p. 173). Therefore, regulators need to incorporate technological changes when adjusting or formulating new accounting rules, policies or standards (Hasan, 2022).

Regarding the predictions that some professions and jobs will disappear, including accounting (Rawashdeh, 2023), Onyshchenko et al. (2022, p. 189) state that the roles of accountants will change but that technologies will not substitute accountants. According to Hasan (2022, p. 462), accounting professionals cannot be replaced by AI when tasks that need human creativity and judgments are in question. This is in accordance with Leitner-Hanetseder et al. (2021), who concluded that some non-core tasks and skills of accountants will be changed and replaced by AI and other digital technologies, while core accounting roles and tasks will continue to exist, even though they might be performed using digital technologies or in collaborating with them. On the contrary, AI will complement accountants' performance, as they can re-engineer the whole record-to-report process by automating repetitive and time--consuming tasks (Kommunuri, 2022, p. 588).

This requires a drastic shift in educational curriculums of academia, professional bodies continuing professional development programs, and training processes (Hasan, 2022). Accountants will transform from basic clerks and data operators to strategic leaders, trusted value advisers, dynamic thinkers and *storytellers* (Halar et al., 2023, pp. 123-124). Accountants have a critical role in ensuring that the usage of AI aligns with organisational values and that immoral decision-making is avoided (Abdullah and Almaqtari, 2024, p. 13).

1.3. Areas of Application of Artificial Intelligence by Accounting Functions

Over the past decade, numerous studies have pointed out that the accounting profession is highly susceptible to automation (World Economic Forum, 2020). This is nothing new – in the 1970s, some pioneering work on AI identified tax accounting as fertile ground for development work, while in the 1980s, spreadsheet software and micro-computers (as they were then called) were enthusiastically embraced by most leading accounting firms (Susskind and Susskind, 2016, pp. 103-104).

In the past, the accounting profession was directly influenced by the development of information technology. In particular, the introduction of Enterprise Resource Planning (further in text: ERP) software has driven the automation of accounting functions in many medium and large companies. This automation manifests itself primarily in the establishment of predefined accounting schemes for repetitive transactions such as outgoing invoices, routine incoming invoices and the recording of bank transactions. This automation results from processes that are well-established in the existing literature and do not fall under the classification of AI.

The ultimate goal of using AI in day-to-day business should be to increase productivity and automate routine tasks. As already mentioned, AI encompasses a broad spectrum of concepts, methods and technologies. From the perspective of the accounting profession, it is imperative to recognise the importance of not only AI

but also blockchain technology and robotic process automation (further in text: RPA) as key technological advances.

As the main functions of accounting include tracking, reporting, executing and predicting financial transactions, the following tasks are likely to be influenced in the future by advances in AI, blockchain technology and RPA.

Function 1: Tracking

Tracking financial transactions is an important but time-consuming component of the accounting process. Despite the acceleration provided by ERP systems, further improvements are possible through the use of innovative technologies such as:

- Integration of AI in ERP systems, especially in the processing of incoming invoices. AI algorithms trained using optical character recognition software on a dataset of scanned invoices and the corresponding postings can be used to automate current period postings.
- Blockchain for more transparency: Blockchain technology introduces a paradigm shift in tracking by enabling the exchange of accounting information between transaction parties (e.g. seller and buyer) in real-time. Blockchain could help accountants gain clarity on their companies' available resources and commitments and also free up resources to focus on planning and valuation rather than recordkeeping (ICAEW, 2018a). This will lead to a shared ledger that can be viewed within networks of companies using a triple-entry ledger based on blockchain technology (Han et al., 2023).
- RPA for repetitive tasks – RPA technology is able to automate structured, rule--based tasks, such as:
  - Copying and pasting documents (e.g. incoming invoices and bank statements) from external sources into the ERP system. Once the documents have been downloaded into the system, other technologies take over further tracking tasks in the system.
  - Filling out online forms, such as the registration of employment relationships with institutions (tax office, pension insurance, etc.) based on the information already recorded by the payroll department.

Function 2: Reporting

The preparation of financial statements and internal reports after the recording of transactions is an important task of accounting departments. This function includes both external and internal reporting.

- External reporting: Automation has already significantly improved efficiency in the preparation of the primary financial statements (statement of financial position, income statement, cash flow statement and statement of changes in equity). However, the automation of the notes to the financial statements is an

area that is ready for further development. Utilising data from ERP systems can streamline the preparation of notes and thus improve the scope and accuracy of financial reports.

- Internal reporting: The need for diverse reporting across different business functions has traditionally required a decentralised approach, often managed by controlling departments. Advances in the skills and knowledge of accounting professionals in the area of data processing provide the opportunity to outsource internal reporting within the accounting function.

Function 3: Executing

The execution function includes tax compliance, payroll administration and financial tasks (i.e. payments) in addition to tracking and reporting (as explained earlier). As an integral part of accounting, tax compliance is one of the most important functions – in an increasingly transparent and legally complicated environment, organisations need to clarify their tax risk management framework with third parties such as regulators, tax authorities, new business providers and service providers (Dwianika et al., 2023).

Function 4: Predicting

With access to historical data, accounting helps predict future financial trends, focuses on budgeting and risk assessment, and helps with strategic planning. With the help of AI, historical financial data can provide insights and forecasts. AI's ability to analyse vast amounts of data outperforms traditional manual analysis in terms of both speed and volume, enabling more nuanced and predictive insights.

Kokina and Davenport (2017) emphasise that the need for human accountants will not disappear in the foreseeable future, but there are certain activities that can already be automated. Table 1.1 shows a systematic overview of the accounting areas and activities that can be automated.

Table 1.1. Areas and activities that can be automated in the accounting function

Area	Activities
1	2
Accounting	■ Automating complex journal entries ■ Performing and documenting accounts reconciliations ■ Calculating and applying allocations ■ Maintaining fixed-asset accounts
Accounts payable	■ Entering nonelectronic-data-interchange invoices ■ Performing 2- and/or 3-way invoice matches ■ Processing expense-approval requests ■ Completing audits (e.g. duplicate supplier payments)
Accounts receivable	■ Generating and validating invoices ■ Applying cash to outstanding balances ■ Analysing and processing disputes ■ Creating reports (e.g. accounts-receivable ageing, credit holds)

1	2
Financial planning and analysis	■ Building standard management reports ■ Consolidating and validating budget and forecast inputs ■ Gathering and clearing data for analysis
Payroll	■ Flagging time-sheet errors and omissions ■ Auditing reported hours against the schedule ■ Calculating deductions ■ Harmonising data across multiple timekeeping systems
Other	■ Preparing external-reporting templates ■ Conducting transaction audits of high-risk areas ■ Preparing wire-transfer requests

Source: authors according to (Plaschke et al., 2018).

Finally, a significant impact of digital technologies can be in the area of incorporating big data from accounting with other data such as free text, images and videos that can be analysed and manipulated (Kroon et al., 2021) to obtain better information and predictions about future trends.

1.4. Areas in Which Artificial Intelligence Will Not Be Used

As can be seen from the previous description of potential tasks that can be automated in accounting, all of these processes must be controlled and managed by people – professional accountants – regardless of the potential of AI, blockchain and RPA in accounting. This is especially true for non-routine accounting tasks as well as for tasks that appear in accounting for the first time (i.e. new business transactions).

Due to the limitations of these earlier forms of AI, non-routine tasks that were difficult to codify seemed to be protected from automation, especially as earlier waves of technology had automated mainly less skilled occupations. The release of ChatGPT in November 2022 changed both the nature and urgency of the discussion. Large language models proved unexpectedly capable in creative, analytical and written tasks and even achieved top scores on university and professional exams (Dell'Acqua et al., 2023). Despite the hype around large language models, only 29 papers on large language models in accounting were published on SSRN in the period from the beginning of 2022 to the end of October 2023 (Dong et al., 2023). This suggests that the use of large language models in accounting is still in its infancy. The future tasks and roles in accounting that will be influenced by large language models are, therefore, still difficult to predict.

Finally, through automation and AI, blockchain and RPA implementation, accounting departments will have the opportunity to either:

- expand their role in finance and financial planning and analysis due to the additional time freed up by automation and AI implementation. This will result in accounting professionals taking on more "generalist roles" compared to their current roles or

- expand their role in data-driven functions, which will lead to a consultative style of accounting that will enable some strategic moves to be proposed to senior management. This new role is described by ACCA as a "data navigator", one of the 5 "career zones" available in accounting (ACCA, 2020a).

1.5. The Competencies of Accountants for The Future

Over the course of their careers, professional accountants use a variety of skills to perform their highly specialised tasks. However, the landscape of accounting and the careers of accountants have changed dramatically over the past decade. "Traditional" competencies of accountants, which include knowledge of accounting standards, accounting regulation and tax laws, and related skills and abilities, are no longer sufficient to successfully perform accounting tasks in the modern business environment. The digitalisation of business and the application of digital technologies in the execution of tasks have had a profound impact on the accounting profession. As a result, professional accountants are now required to have broadened knowledge, skills and abilities (further in text: KSAs) or, in a word, competencies in order to improve the quality of their services and fit into the modern business environment.

As organisations adopt new digital technologies into their business, accountants must learn to use them to stay relevant and competitive. Many authors (Chabus, 2021; Cordos and Tiron-Tudor, 2023b; Gonçalves et al., 2022; Luhova, 2023; Rumbens et al., 2019; Tavares et al., 2023) have highlighted that in the age of digitalisation and the increased use of digital technologies such as blockchain technology and AI, professional accountants are expected to develop new skills such as interpersonal skills, attention to detail, time management, leadership, critical thinking, problem--solving, communication, collaboration and propensity for teamwork.

According to UNESCO (2018), digital skills are defined as "a range of abilities to use digital devices, communication applications and networks to access and manage information." Mastering the digital skills of accountants in a changing world is a continuous process (ACCA, 2020b, p. 45). Digital skills are crucial for the efficient use of new tools and technologies and for keeping up with the latest trends in an ever-changing business world. Digital literacy is important for gaining a better insight into the company's overall operations and consequently making informed business decisions. The use of powerful analytics tools (e.g. Microsoft Power BI, Sage Intelligence or SAP Analytics Cloud) enables the identification of trends and patterns in financial data and is also useful for analysing key performance indicators. ICAEW (2018b) points out that the digital skills of accountants help maximise the business benefits from the use of technological innovation in the following areas: automation, anticipation of risks and opportunities and advisory services.

Given the changes brought about by the application of digital technologies and the digital transformation of business, it is clear that traditional business strategies

and models are being disrupted, and accountants have the potential to become 'in--house management consultants' in the future (IFAC, 2019). The traditional role of the accountant as a provider of information is changing, and the accountant of the future is becoming a data scientist who has developed strong business analytics skills (Oesterreich and Teuteberg, 2019). Analytical skills of an accountant are the ability to gather information to identify the problem, then through detailed analysis of that information, find out the relevant facts and offer the best solution to the problem. These skills help accountants assess and evaluate data in order to make operational and strategic business decisions that increase the company's success.

Al-Htaybat and von Alberti-Alhtaybat (2017) highlight similar skills that accountants for the future will have to develop: analytical skills, communication skills (telling a story) and creative and open mind (creativeness). Effective communication (written and verbal) is paramount for accounting professionals. They should be able to listen, present ideas in a clear and concise way, present complex financial information clearly and concisely and adapt their communication style to different audiences. Accountants collaborate with almost all departments within the organisation (e.g., in creating business strategies, budgets, and cash flow projections), so good collaboration with other employees is of utmost importance to them. Time management is crucial for accountants, as many accounting tasks have to be completed within a strictly defined deadline.

When analysing the relevant literature, a large number of different skills were identified that are required of accountants in the digital age. In order to gain a better overview, it is necessary to group them. Tsiligiris and Bowyer (2021) list four categories of skills required for the accountants of the future, namely: (1) *ethical skills,* (2) *digital skills,* (3) *business skills* and (4) *soft skills.* Within each of these key categories of skills for future accountants, subcategories of specific skills are listed in Table 1.2.

Table 1.2. Categories and subcategories of skills identified as important for future accountants

Category of skills	Subcategories of skills
Ethical skills	■ technical ethical skills ■ interpersonal ethical skills
Digital skills	■ basic digital skills ■ advanced digital skills ■ data skills
Business skills	■ consulting and business advisory skills ■ strategic thinking
Soft skills	■ adaptability ■ communication ■ lifelong approach to continuous personal and professional development ■ critical thinking ■ dynamic problem-solving ■ emotional intelligence

Source: (Tsiligiris and Bowyer 2021, p. 631).

In the course of their work, accountants have access to very sensitive company financial data as well as personal data. Under these circumstances, individuals could misuse or manipulate this data. In addition, the use of new digital technologies related to advanced big data analytics has led to ethical challenges for the accounting profession (Tsiligiris and Bowyer, 2021). For this reason, accountants must adhere to strong ethical standards in the fulfilment of their daily duties. Tsiligiris and Bowyer (2021, p. 632) pointed out that future accountants should have "a set of ethical skills that can be summarised in two broad dimensions: (1) technical and (2) interpersonal ethical skills". Technical ethical skills include "knowledge of the ethical guidelines and code of conduct of accounting professional bodies", while interpersonal ethical skills include asking the right questions to maintain the quality of data generated and used by digital technology (Tsiligiris and Bowyer, 2021, p. 632).

According to Tsiligiris and Bowyer (2021), digital skills for future accountants comprise:

- basic digital skills related to the use of key digital technologies such as ERP systems, standard business intelligence applications, cloud-based accounting solutions, digitisation of tax return activities, etc.
- advanced digital skills mean that accountants are familiar with newer and more advanced digital technologies such as AI, blockchain technology, advanced business intelligence, programming, etc.
- data skills incorporate data management skills (e.g. accuracy, relevance, consistency) and data analysis.

The range of technical skills of accountants should be extended by basic digital skills (Dow et al., 2021), advanced digital skills (Yigitbasioglu et al., 2023) and data skills. Huerta and Jensen (2017, p. 102) emphasise that "extracting meaningful knowledge from big data requires not only a deep understanding of the data but also a creative way of thinking about data. The challenge with big data is identifying the right questions to ask."

The role of accountants is changing with digital innovations, so the tasks of accounting are shifting from routine tasks to value-adding activities for organisations (Andreassen, 2020). Accountants need the KSAs to meet the need for timely and accurate data and to present it in understandable, non-technical language. According to Tsiligiris and Bowyer (2021), two sets of business skills have emerged as critical for future accountants: consulting and business advisory skills and strategic thinking. In the future, accountants are expected to be directly involved in the decision-making process, so strategic thinking will become increasingly important (Halar et al., 2023, p. 121). Strategic thinking means being able to see the bigger picture, and strategic direction sets the direction in which the organisation is heading in the long term.

Many authors and reports emphasise the increasing importance of accountants' soft skills. Soft KSAs include interpersonal and communication skills, including the ability to fit in and adapt to the company's organisational culture (Halar et al.,

2023, p. 121). Among the soft skills of accountants, adaptability, critical thinking, dynamic problem solving, lifelong approach to continuous personal and professional development, and emotional intelligence stand out (Tsiligiris and Bowyer, 2021):

- adaptability – accountants need to be adaptable to the changing business environment and challenges emerging from the digital transformation of businesses and changes in business models
- communication – accountants act as a link between internal and external stakeholders and need to use effective 'storytelling' to present complex and diverse data in a non-technical and engaging way
- lifelong approach to continuous personal and professional development – accountants need to take the initiative to keep learning (reskilling and upskilling) in order to meet the changing needs of the labour market
- critical thinking – one of the most important skills of accountants in the future
- dynamic problem-solving – in the digital context, accountants need to be able to make decisions under uncertainty and taking into account a dynamic set of factors
- emotional intelligence – the accountant's ability to recognise, regulate and manage their own emotions and those of others and to harness and apply them to tasks.

The use of advanced digital technologies in business is important not only for the accounting profession but also for universities, study programs, and students. In this environment characterised by accelerated digitalisation and the use of digital technologies, there is a need to change the current accounting curricula in universities to provide students with the necessary technical but also soft skills for a successful career in accounting in order to shape the future (Damerji and Salimi, 2021; Surianti, 2020) and adapt to the new reality as efficiently as possible (Ellitan and Anatan, 2020). Jackson et al. (2023) and Tsiligiris and Bowyer (2021) emphasise the need for extensive and relevant collaboration between employers, professional bodies and associations, and universities to provide accounting education that meets the needs of the market in terms of KSAs of accountants for future. Universities and other educational institutions need to update accounting study programs to prepare students for their new roles and future careers. The focus of changes in study programs should be on the development of critical and systemic thinking and the development of students' creative skills (Gulin et al., 2019).

1.6. Conclusions

The corporate business environment in the contemporary AI era is faced with different disruptions for different industries and companies, as well as for their core operational and support infrastructural business functions. For companies

to be successful, it is important to strategically and holistically plan the overall transformation of every function and operation in a company. The overall accounting profession is deeply impacted by Industry 4.0 and Industry 5.0 conditions, principles and components, including particularly AI and its humanised view of technological changes. As companies plan to adopt and implement AI and other digital technologies in their day-to-day core business operations, governance structures also need to holistically plan the overall transformation of companies' support business functions, including accounting. The accounting function is 'a heart and a blood flow' of every company, as financial and other information from all other functions are gathered or 'flow' into the accounting information system, where information is analysed and prepared in the form of financial and non-financial statements and then 'flow' out for decision-making process of various internal and external stakeholders. Therefore, to be able to operate properly, accounting functions and accountants also need to adapt and transform to add value to governance structures in the AI era.

The perceptions, roles and competencies of accountants, as well as perceptions and tasks of accounting functions in companies, are radically transformed. Digital technologies, including AI, will become a standard toolkit for future accountants – dynamic and strategic value advisers of companies' governance structures. Their competencies set will be drastically changed, so education curriculums and continuing professional development programs also need to be revised and adapted for the accounting tasks in the next industrial revolution. Repetitive and time-consuming accounting tasks will be automated by AI technologies that will increase the effectiveness and efficiency of the accounting function. Furthermore, to be relevant in the contemporary era, the accounting profession needs to adjust or write completely new accounting rules, policies and standards for the next industrial revolution driven by AI and human-technology interaction.

The rapid advancement of technologies such as AI, blockchain and RPA heralds a transformative era for the accounting profession. They promise to automate routine tasks and free up accountants to focus on strategic advisory tasks. Despite these advances, professional accountants remain indispensable to managing complex, novel transactions and ensuring ethical and regulatory compliance.

The future of accounting is likely to lie in financial planning and analysis as well as data-driven advice, emphasising the growing importance of multi-faceted and advisory roles in the age of technology. This shift emphasises not only the need for accountants to constantly learn and adapt but also the critical role they play in interpreting complex data to ensure the transparency, accuracy and reliability of financial reporting.

Traditionally, accountants have a strong technical background. The dynamic business environment and the increasing use of digital technologies in business require accountants to complement their technical skills with numerous other skills in order to survive and be relevant in these circumstances. When complemented with the right combination of ethical, digital, business and soft skills, accountants are in

a unique position to add value to organisations and their stakeholders. Advanced KSAs of accountants can help organisations in various areas – identify cost savings for better efficiency, reduce operating costs, minimise risks, optimise business decisions and business performance, increase profits and revenue streams, and identify patterns and trends. In conclusion, it can be said that the use of digital technologies in business has changed the role and tasks of accountants in business processes.

This chapter debates a comparative review of the literature and a critical examination of the state and perspectives of accountants in organisations, the competencies of accountants and the way accounting tasks are performed in the era of the fourth and fifth industrial revolutions, primarily disrupted by AI. Presented results can be useful for professional bodies, regulators, and educational institutions dealing with the accounting and accounting profession. With the aim of closing the gap between theoretical and applied research, further research should focus on exploring the market situation to find out how to manage organisational change in the era of smart digital technology adoption. It is necessary to examine the overall competencies of current accountants, the degree to which they use digital technologies to perform their tasks and the importance of accountants in adding value to the organisation in the digital age.

The research in this chapter is not without limitations. Firstly, in the era of big data, our analysis is not comprehensive, as we did not manage to analyse all published literature on the research topic in all relevant databases, so additional bibliometric and systematic methodological approaches to the research are welcomed. Secondly, we analysed secondary literature and gained insights from this type of literature, but primary research would also enrich the research field. Furthermore, additional and broader themes could be studied in more detail, including the advantages and disadvantages of AI impacts on the accounting profession.

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Chapter 2

Artificial Intelligence Application in the Auditing Profession

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Technological advances are changing the world at an accelerating pace. Business growth comes with complexity in operations, and leveraging technology-based decision tools is becoming prominent in today's business world (Alaba and Ghanoum, 2020). Technology is becoming an increasingly important aspect of internal and external audits as clients become more sophisticated users of technology; auditors face significant pressure to reduce audit fees, and technology is better able to perform audit tasks (Eulerich et al., 2022). Hence, with modern technologies such as Artificial Intelligence (AI), the discipline of accounting and auditing has been developed tremendously (Han et al., 2023; Munoko et al., 2020). Also, audit firms are responsible for staying abreast of this change with equal investment in advanced technology-based tools to effectively examine the high volume of data generated for efficient analysis of a company's businesses and its risks (KPMG, 2016). Consequently, the auditing profession is tuning into this change by integrating AI systems to stay abreast of the transformation (Alaba and Ghanoum, 2020).

AI research aims to enable machines to execute complex jobs that would otherwise require intelligent humans. Also known as machine intelligence, AI integrates human--like intelligence into machines (Alab and Ghanoum, 2020). Making companies' systems digital has enabled them to adopt new technological tools to simplify business processes and transform business models to innovate their operations because they can increasingly access advanced computing power and large databases (Han et al., 2023).

Accounting and auditing are critical roles that ensure a corporation's reliability, credibility, and financial stability (Hashid and Almaqtari, 2024). Historically, these functions were primarily dependent on manual processes and human expertise. However, as information technology (IT) has grown, a paradigm shift in handling accounting and auditing has occurred. Recognising the relevance of IT in this context, organisations, accountants, auditors, professional bodies, academics, and regulators have switched their focus to improving auditing and accounting processes using technology (Al-Hattami, 2023).

Auditing is particularly suited for data analytics and AI applications because it has become challenging to incorporate vast volumes of structured and unstructured data to gain insight into companies' financial and non-financial performance. Also, many audit tasks are structured and repetitive and, therefore, can be automated (Kokina et al., 2017).

The Big 4 audit firms have invested significantly in AI for advisory and assurance practices (Fedyk et al., 2022; Issa et al., 2016). In the assurance practice, AI is used to perform auditing and accounting procedures such as reviewing general ledgers, tax compliance, preparing work papers, data analytics, expense compliance, fraud detection, and decision-making (Munoko et al., 2020). Several research papers have reported that significant certified public accountant (CPA) firms, such as KPMG, PWC, and others, are starting to intelligently automate their business processes by incorporating AI and cognitive capabilities (Kokina and Davenport 2017; Moffitt et al., 2018). Each of the Big 4 accounting firms has invested heavily in technological innovation (Kokina et al., 2017). Undoubtedly, accountants and auditors are among the many business occupations most affected by AI and recent technological developments (Frey and Osborne, 2017). Therefore, this chapter seeks to provide answers to the following research question:

RQ: What are the most critical AI applications in internal and external auditing?

This research question leads to the chapter's main objective, identifying the critical AI applications in external and internal auditing based on empirical studies conducted over the last four years. The chapter consists of four parts. Section 2.1 elaborates on the use of AI tools in the auditing process. The following two sections present the opportunities for applying AI technologies in external auditing (2.2) and internal auditing (2.3) based on the results of empirical studies included in the literature. The last section (2.4) concludes the chapter and emphasises why integrating AI technologies in auditing holds immense potential to revolutionise audit practices.

2.1. The Auditing Process and Artificial Intelligence

Auditing is a systematic and independent process of obtaining and evaluating evidence regarding an entity's actions or properties and communicating the results of that evaluation to relevant stakeholders (Mökander et al., 2023). Auditing can be considered a governance mechanism because it can monitor conduct and performance. Auditing has a long history of promoting procedural regularity and transparency in financial accounting and worker safety (Mökander et al., 2023).

An internal audit is an independent, objective assurance and consulting activity designed to add value and improve an organisation's operations. It helps an organisation accomplish its objectives by bringing a systematic, disciplined approach to evaluate and improve the effectiveness of risk management, control, and governance processes (IIA, 2024).

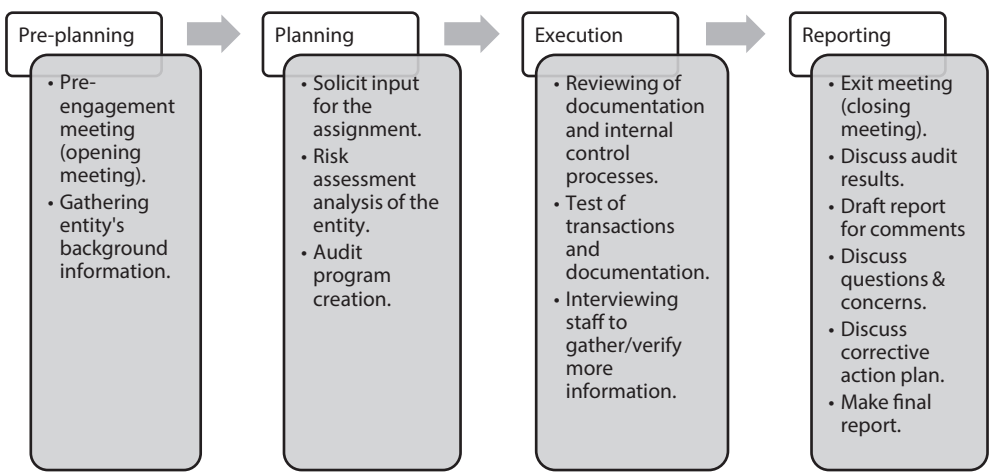

Figure 2.1. Audit process stages

Source: own presentation based on (Alaba and Ghanoum, 2020).

Understanding the audit process helps determine the AI applications used in auditing. The audit's primary purpose is to gather evidence to form a proper opinion on the organisation's financial statements. The pre-planning, planning, execution and reporting stages are crucial audit stages (Figure 2.1). First of all, an auditor must assess whether he will rely on the internal audit function's work. At pre-planning, an auditor evaluates the entity's internal procedures and policies. Then, an auditor conducts the entity's risk assessment and determines the overall strategy, including the audit work's scope, nature and timing. In carrying out the audit assignment, an auditor should properly understand the client's nature, history, and internal control processes and examine transactions and documentation to gather evidence to

support the audit opinion. An auditor interviews the entity's personnel to verify or gather additional information. An auditor also collects documentation collected by the audited entity as part of its internal audit. As part of the final reporting stage, an auditor conducts a closing meeting, presents the audit results, prepares a draft report for comments, establishes a corrective action plan, and prepares the final report (Alaba and Ghanoum, 2020).

Many audit processes are structured and repeatable, making them suitable for AI and data analytics applications. Although current auditing standards require sampling using a conventional human approach, there are situations where technology helps analyse large amounts of data in a limited time (Kokina and Davenport, 2017).

The term 'artificial intelligence' was coined in 1956 by John McCarthy, one of the founders of AI research, who defined AI as 'getting a computer to do things which, when done by people, are said to involve intelligence' (Holmes and Douglass, 2022). The organisation's work helped establish the foundation for later research on AI. The development of AI has proceeded in stages over the years. Initially, problems were solved, and decisions were made without considering the knowledge and experience accumulated at the time. The second phase lasted until the 1970s and focused on studying emerging expert systems. AI was applied to practical applications such as disease diagnosis and treatment. In the 1980s, fifth-generation computers made it possible to introduce AI to the open market. The emergence of "knowledge-information processing computer systems" in Japan in the early 1980s led to advances in AI research. Fifth-generation computer development program at the time was aimed at enabling the speed of logical reasoning at the speed of numerical calculations. The development of Internet Technology in the 1990s led to the further development of AI, from single agents to a web-based environment for distributed AI. The evolution of computer technology and intelligent computers in the 21st century raises interest in AI technologies, such as voice and text recognition (Almufadda and Almezeini, 2022).

IBM defines AI as a technology that enables computers and machines to simulate human intelligence and problem-solving capabilities. On its own or combined with other technologies (e.g., sensors, geolocation, robotics) – AI can perform tasks that would otherwise require human intelligence or intervention (IBM, n.d.).

Saranya and Subhashini (2023) defined AI as a method that refers to a system or a machine that imitates human intelligence to perform functions in the real world. AI allows the system to be trained from the data and to think and learn from the experience to solve particular problems. It can heuristically refine itself based on the data used.

AI aims to investigate theories and develop computer systems that can conduct tasks that require biological or human intelligence, with functions such as perception, recognition, decision-making, and control (Fan et al., 2020).

AI technology covers several fields, including Machine Learning (ML), Deep Learning (DL), Artificial Neural Networks (ANN), Natural Language Processing (NLP), and Expert Systems (ES) (Figure 2.2).

ML is a feature of AI that arose from the concept that machines can learn like humans. It enables the automation and continuity of the learning process from historical data without being explicitly programmed by humans (Hasan, 2022). ML focuses on more advanced predictive analytics.

DL technology is an extension of ML that uses artificial neural networks to complete representation learning from data (Liu et al., 2022). It is a type of ML that uses algorithms that can simulate an array of neurons in an ANN that learns from vast data sources. Algorithms also approximate the structures and functions of the human brain (AICPA, 2020). It allows for better predictive performance and audit judgment support by allowing DL to use textual analysis (Holmes and Douglass, 2022). DL is a subset of ML and is about computers learning to think using architecture modelled after the human brain. ML can assist in transaction classification with the scope of control function (Hasan, 2022).

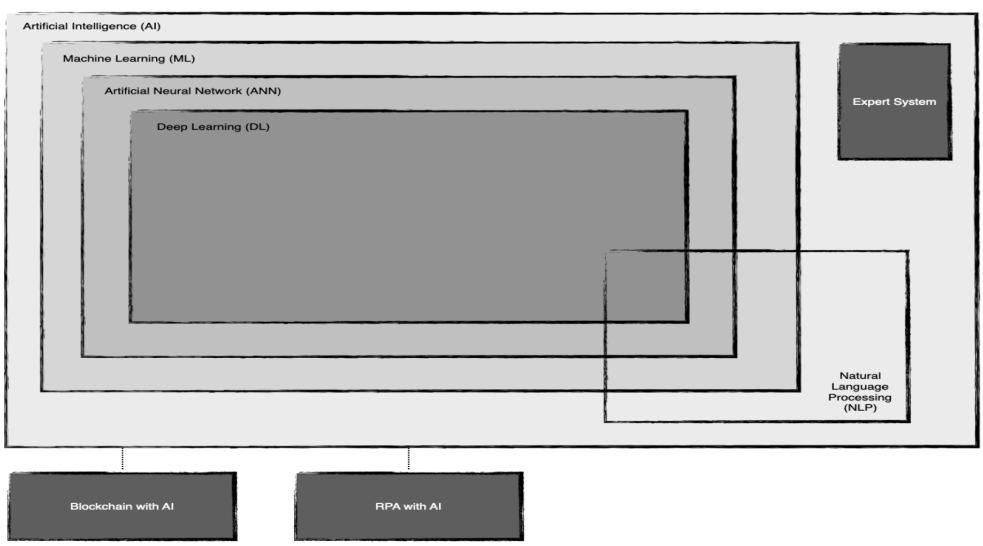

Figure 2.2. AI technologies fields

Source: own presentation based on (Almufadda and Almezeini, 2022).

Under the neural network concept of AI, computer systems mimic the neural connections in the human brain. It is an ML algorithm based on the human neuron model. A neural network is a computational system for processing information as a response to external stimuli, which consists of a set of highly interconnected processing elements called neurons. They imitate specific performance characteristics of biological neural networks. Examples of neural networks are handwriting and facial recognition (Almufadda and Almezeini, 2022).

NLP allows AI to analyse the unstructured text, improve compliance and handle financial inquiries, and automatically detect transactions that violate regulatory standards, reducing noncompliance risks (Abdullah and Almaqtari, 2024). NLP technology teaches artificial models to understand and process human speech and focuses on replicating human natural language and communication methods. It can be applied in processing unstructured text information, systematic and automatic retrieval and review of documents, high-risk identification and others (Hasan, 2022).

ES should be understood as applications that acquire the know-how and experience in a specific field, use this knowledge in problem-solving, and assist the user in decision-making. ES consist of a knowledge base and an inference engine. The database stores information obtained from experts in a particular field, and knowledge engineers organise information into rules. Conclusions are drawn from the rules in the database using the inference engine. Many commercial ES are available on the market, such as airline scheduling, cargo placement, and medical diagnostics (Almufadda and Almezeini, 2022).

A Decision Support System (DSS) is an interactive, flexible, comprehensive computer system supporting decision-making. It helps solve an unstructured management problem. DSS establishes alternatives and outcomes for a problem so that a decision can be made. ES aim only to automate decision-making and ultimately replace the human decision-maker (Hasan, 2022).

The emergence of a new digital age enabled organisations to use new technologies through access to advanced computing power and large databases. Through them, business processes have been simplified, business models have been transformed, and operational activities have been innovated. Today's global enterprises operate based on the Internet and platforms. Blockchain is now regarded as the fifth pillar of the IT revolution and is also expected to become the foundational technology of the next-generation Internet. Blockchain is described as a distributed ledger technology or a type of financial technology. Others view blockchain as a sequential database or a giant spreadsheet that surpasses the classical financial ledger by recording transactional information, secured by cryptography, and governed by a consensus mechanism. Blockchain is characterised by transparency, decentralisation, immutability, tamper resistance, strong authentication, synchronised networks and consensus. It enables the transfer of data and information that has value. This category can include finances and assets such as intellectual property, health data, voices and ideas. Blockchain technology combined with AI-based processes increases confidence in data, models and analysis, giving a more flexible and precise audit model that automates assurance (Han et al., 2023).

Robotic Process Automation (RPA) is a software developed to automate repetitive, standardised, structured and rule-based tasks on one or more software platforms. It should be noted that RPA and AI are two different technologies. While RPA is

process-based, and its job is to automate tasks based on rules, AI technology is based on high-quality data to enable it to learn patterns and simulate human decisions. RPA and AI complement each other (Zemánková, 2019).

Technology is becoming increasingly important for internal and external auditing as clients become more sophisticated technology users. Auditors face significant pressure to reduce audit fees and use more technology to perform their tasks (Eulerich et al., 2022).

2.2. Major AI Applications in External Auditing

American Institute of Certified Public Accountants stated that AI, as a critical technological driver, enables continuous audit and data analysis. Available AI technologies offload tasks to humans by automating tasks based on collected data in accounting, tax and audit. Among the functionalities AI offers is identifying unusual transactions while considering applicable standards and historical records. AI can analyse board meeting minutes or critical communications to help identify additional risks (AICPA, 2023).

The possibilities of processing massive financial data volumes and facilitating the identification of patterns, trends, anomalies, and decision-making abilities in accounting and auditing have been increased by AI technology. These technologies include ML, DL, big data analytics, data mining, and cloud computing.

A recent study provided evidence of the effectiveness of applying ML to learn data patterns and predict financial reporting quality (Huang and Wang, 2023). ML models outperformed traditional regressions in earnings prediction.

DL can be used in multidimensional auditing. Image and speech recognition of DL can be used to improve the audit process in general, including, for example, in fraud interviews. Doubtful answers or a significant delay in providing them could indicate fraud. Using facial pattern analysis and detecting nervousness in image analysis could also support the auditing process (Dickey et al., 2019).

Several studies provided evidence of the usefulness of AI in recognising patterns in documents. NLP supports the analysis of contracts and financial records, allowing recognition of the document's context and extracting critical information (Kokina and Davenport, 2017). NLP technology and text analysis were combined to facilitate the audit of many low-risk documents. They were applied to a set of reinsurance agreements, and the study's results confirmed their feasibility within the set scope, detecting anomalies and generating evidence. However, some limitations were noted due to the current audit standards and methodologies of the risk-based audit approach. These limitations discourage using this technology for population-wide audits (Almufadda and Almezeini, 2022). The international audit standard ISA 530 talks about statistical and non-statistical sampling by the auditor to provide a reasonable basis for concluding the population from which the sample was selected (IFAC, 2009).

ES can have many adoptions in auditing. It can be used in audit planning, obtaining evidence, assessing audit risk, issuing an audit opinion, and preparing an audit report. In financial accounting, an expert system can design accounting information systems and financial statements, process invoices and enter entries, assess standards, and develop spreadsheets (Hasan, 2022).

RPA has been considered particularly useful in the audit field. RPA can facilitate the automation of audit tasks such as preparing data and files, integrating data from multiple files and running basic audit tests in Excel (Zemánková, 2019). As part of RPA's functionality, applications are run in such a way as to allow user interactions at the interface level, similar to how a human works in software. This RPA's characteristic makes it more user-friendly. Additionally, RPA-based solutions to support workforce automation are cheaper, faster and more accessible. RPA's investigations in the audit automation process confirmed the impact on improving the quality of the auditor's examination, more precise assessment, and removal of risks associated with material misstatements of income (Zhang, 2022). Accountants with no coding background can use RPA tools to automate routines and time-consuming tasks, such as data entry, verifying and processing transactions, and managing inventory. For example, auditors can use RPA to perform a three-way matching test for pricing and quantity information from invoices, purchase orders, and shipping documents (Ng, 2023).

Hashid and Almaqtari (2024) identified the following AI applications in auditing:

- AI-powered automation solutions and RPA systems extract, categorise, and enter data, enabling faster financial forecasting and the identification of anomalies in financial records.
- AI improves decision-making by analysing massive amounts of data and discovering real-time patterns. Continuous auditing (CA) tools built based on AI allow real-time monitoring of financial activities and reduce errors, allowing for a more thorough evaluation of financial data.
- AI predicts future trends based on historical data, improves financial forecasting and budgeting, and detects fraudulent transactions.
- NLP allows AI to analyse unstructured text, improve compliance, and handle financial inquiries.
- AI automatically detects suspicious transactions that violate regulatory standards and reduces noncompliance risks.
- RPA systems automate regular bookkeeping activities and minimise the need for human involvement.
- AI algorithms rapidly analyse big datasets and detect patterns, trends and abnormalities, allowing auditors to discover potential fraud.
- AI algorithms automate typical accounting processes, such as data entry and transaction processing, saving time and decreasing human error.
- AI systems assess massive amounts of financial data efficiently and quickly, detect patterns, anomalies, and trends that people may miss, and aid in detecting and evaluating fraud.

- AI provides real-time insights and predictive analytics to help decision-makers make informed decisions.
- AI helps in financial forecasting and scenario analysis, producing reliable financial predictions.
- AI enhances audit efficiency and effectiveness by assessing financial statements, identifying potential hazards, and recommending areas for additional examination.

Gao and Han (2021) studied AI's influence on auditing financial statements, particularly ways of achieving audit objectives, including implications on audit instructions, sources of audit evidence, formats of audit evidence and audit judgements. The main results of their studies are the following:

- AI influences the objectives of auditing financial statements. AI can provide technical support and safeguard measures to assure the overall fairness of the entity's financial statements. With the increasing synergy between AI and audit practice, audit objectives should be positioned to ensure the reliability and fairness of accounting information rather than compliance with accounting information preparation procedures to reduce audit expectations and bridge the gap between the accounting profession and the legal profession.
- AI influences the identification of audit instructions. Vital AI analysis function via Big Data searching could not only satisfy the requirements in the completeness of the set of auditing instructions but also realise the close convergence between the audit instruction system and audit objective system, pushing auditing practices towards extreme proximity to the ultimate auditing purpose of the authenticity of accounting information.
- AI influences the source of audit evidence. Using AI, auditors can inspect irregularities and conduct deep mining on the three dimensions of accounting information to hunt for audit evidence with a pre-defined purpose.
- AI influences the format of auditing evidence. AI has generated opportunities for broader expert engagement in auditing, paving the way to explore more ways to gather auditing evidence. Under such new circumstances, expert conclusions may be introduced as a new form of evidence for financial statement auditing.
- AI influences the auditing judgement. Comprehensive inference aided by AI, a model with rationalism as the core, can render a practitioner's judgement less subjective, arbitrary and complex to verify.

Issa et al. (2016) proposed a general audit process comprised of seven phases with an AI application that transforms auditing into a highly efficient and effective process.

Phase 1: Pre-planning. Pre-planning aims to acquire initial knowledge of the client and their industry. In traditional audits, an auditor examines the client's industry, organisational structure, operational methods, and accounting and financial systems. AI can collect, aggregate, and examine Big Data from various exogenous sources and incorporate the above client's information to estimate the initial risk level associated with that client.

Phase 2: Contracting phase. It uses the output from the previous phase, i.e., the initial risk level. In a traditional audit process, an auditor could prepare an engagement letter based on the estimated client risk and sign a contract. AI estimates the engagement's required hours, calculates audit fees, and generates a client-specific engagement letter. Both auditor and client sign the AI-prepared contract.

Phase 3: Understanding internal controls and identifying risk factors. This phase involves planning all aspects of the audit engagement. In the traditional audit process, an auditor assesses documentation, aggregates information, identifies risk factors and determines the internal controls' scope, nature, and timing of substantive tests. AI uses pattern recognition through text mining, image recognition techniques, and visualisation methods to identify risk factors. Finally, all this information is aggregated to identify fraud and illegal-act risk factors.

Phase 4: Control risk assessment. This phase examines the client's internal control system design and implementation. In the traditional audit process, an auditor examines the client's Internal controls policies and procedures, assesses risk, tests controls, reassesses risk and documents the controls testing. AI-based continuous control monitoring system examines the complete population of records to identify any control violations and reports them. AI runs process mining to ensure the internal control system is appropriately designed, configured and implemented correctly.

Phase 5: Substantive tests. Within this phase, data provenance and quality are examined as they are collected, eventually in real-time (by AI). In the traditional audit process, an auditor tests the details of sampled transactions, balances (at a certain point of time), analyses of procedures, and periodically performs sample-based tests (nature, extent and timing depend on internal controls tests). AI can examine 100 per cent of the population continuously. This continuous and comprehensive test of details decreases the likelihood of an abnormal record passing undetected. Incorporating pattern recognition, visualisation, benchmarks, and outlier detection methods on top of analytical procedures can significantly increase audit effectiveness.

Phase 6: Evaluation of evidence. This phase will be included in the previous phase due to the importance of ensuring data quality before running the substantive tests. In the traditional audit process, an auditor must evaluate the collected evidence's sufficiency, clarity, and acceptability. Then, an auditor may either collect more evidence or withdraw from engagement. AI offers an evaluation of evidence in the previous phase instead.

Phase 7: Audit report. The final step in the audit process is issuing a verdict based on the findings from the previous steps. In the traditional audit process, an auditor aggregates previous information to issue a categorical report: clean, qualified, and adverse. AI can generate audit reports in a continuous way rather than categorical.

2.3. Major AI Applications in Internal Auditing

AI can also have numerous applications in internal auditing. AI may help internal auditors find and understand patterns and anomalies in data sets, identify risk areas more quickly, and show where to focus on complex tasks. Moreover, AI can help internal auditors dig deeper into unusual transactions, identify emerging threats and dangers, and provide actionable information to reduce risks and simplify procedures (Patil et al., 2023). AI can help achieve human-level capabilities through data interpretation, learning and adaptation capabilities, and AI integration with information systems (Minkkinen et al., 2022).

Internal audit functions may be the most suitable for performing CA of AI systems (Minkkinen et al., 2022). Along with the possibilities offered by AI, there are also new risks and potential harms to individuals and societies related to AI applications. AI auditing can be defined as a systematic and independent process of obtaining and evaluating evidence regarding an entity's actions or properties and communicating the results of that evaluation to relevant stakeholders. Note that the entity in question, i.e., the audit's subject, can be either an AI system, an organisation, a process, or any combination thereof (Mökander et al., 2023). CA includes collecting and evaluating data, ensuring systems' real-time efficiency and effectiveness, and automatically performing controls and risk assessments. Two main activities emerge with CA: continuous control and risk assessments focusing on auditing systems as early as possible and highlighting processes or systems that experience higher-than-expected levels of risk. Auditing AI and CA are a natural match because CA can potentially keep pace with the AI system's evolution and continuously provide up-to-date information on its performance according to set criteria (Minkkinen et al., 2022).

2.4. Conclusions

This chapter aimed to find answers to the research question on the most critical AI applications in internal and external auditing. Based on the analysis of research conducted around the world over the last four years, it can be concluded that although AI covers many technologies and not all of them apply to auditing, many studies indicate that many elements of AI technology are used in audit practice, which include: robotic process automation, machine learning, deep learning, natural language processing and expert systems. However, the degree of this application depends on the type of audit. In an external audit, AI can support each stage of the audit process, from pre-planning through data collection, risk analysis and formulating audit opinions to preparing an audit report. Moreover, AI influences the audit process, its objectives, sources and format of audit evidence, and professional judgment. Particular attention is paid to supporting the auditor in decision-making, automating many routine audit activities and detecting patterns, trends and unusual transactions based on analysing large amounts of data.

Although, in the opinion of practitioners, some AI applications in external auditing can be successfully used in internal auditing, there is currently no empirical evidence confirming such practices. Additionally, the literature proposes that internal auditors should continuously audit AI systems to continuously monitor the functioning of these systems and enable quick corrective actions.

The current level of development of AI allows us to analyse numbers, digest words and images, and perform digital and physical tasks. AI in audits supports humans, automates repetitive tasks, and can learn from context. However, it is a question of the future to create AI that will have self-awareness.

As P. Bednarek and P. Miszczuk state in Chapter 3, integrating AI technologies holds immense potential to revolutionise audit practices, enabling auditors to navigate the evolving landscape of financial complexity and regulatory scrutiny with confidence and precision. As AI continues to evolve, auditors must adapt and embrace these technologies to unlock new opportunities for innovation and value creation in the audit profession.

As this literature review was conducted based on articles published in the top 25 journals on the BYU Accounting Ranking between 2010 and April 2024, this selection constitutes a limitation of this study. In the future, it is possible to systematise the current state of knowledge in this area, taking into account a more extensive scope of research conducted in recent years that has been published in other journals and conference materials in English and other languages.

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Chapter 3

Benefits and Challenges of Artificial Intelligence Application in the Auditing Profession: Literature Review

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Due to the rapid technological evolution, the world is witnessing changes in business operations. The use of artificial intelligence (AI) technology transforms the way that businesses analyse and process information. The growth of AI technology and its wide application has made the trend of replacing human work with robots more visible (Almufadda and Almezeini, 2022). As part of the adaptation, all disciplines and professions are restructuring or improving their strategies, organisations, products and procedures. In recent years, the Big 4 accounting firms – KPMG, Deloitte, Ernst & Young, and PricewaterhouseCoopers – have been increasingly investing in AI technology (Almufadda and Almezeini, 2022). What about the small and medium practices and internal auditors, who may need more funds or relevant competence to implement AI technologies? If these investments are voluntary, company managers and shareholders may require additional arguments to justify AI implementation due

to the need for economic benefit. Therefore, the literature suggests that decision--makers should use cost-benefit analysis to assess the impact of applying AI in auditing on their current and future performance. A cost-benefit analysis should include all benefits to provide persuasive arguments for AI applications. Despite the potential benefits of AI applications, decision-makers should consider all the challenges related to this decision.

Therefore, this chapter seeks to answer the following research question: What are the benefits and challenges of AI application in the auditing profession?

This research question leads to the following main objective of the chapter: to identify the benefits and challenges of AI application in external and internal auditing based on empirical studies conducted over the last four years.

It is important to note that this analysis included both the theoretical studies, which presented potential benefits and challenges of AI applications in the auditing field and the empirical studies, which demonstrated their positive effects and threats.

This literature review followed a rigorous methodology with the following stages.

The search for relevant studies was conducted using AI Research Assistant, which contains a database of over 60,000 articles from the top 25 journals on the BYU Accounting Ranking.

The search terms used in the search included various terms related to AI application in the auditing profession: 'audit' AND 'artificial intelligence' OR 'machine learning' OR 'artificial neural network' OR 'robotic process automation' OR 'natural language processing' OR 'deep learning' OR 'expert systems'.

The following inclusion criteria are as follows. The inclusion criteria for the study were original and peer-reviewed literature reviews, research articles, and working papers accessible to Wroclaw University of Economics and Business and written in English. The publications had to be from 2021 to April 2024 to ensure up-to-date research.

After the initial research, we narrowed our selection to 99 articles by reading the abstracts of the articles while adhering to our eligibility criteria. These criteria included focusing on AI applications in the auditing field.

With the help of an AI Research Assistant, we narrowed our selection to 17 articles by searching the articles describing the benefits and challenges of AI applications in the auditing field.

After reading the selected papers, we added relevant research papers published before 2021, one literature review published in 2012, and one published online in a non-peer-reviewed journal.

We decided to focus on sources that conducted research in all possible countries, such as the US, Saudi Arabia and Taiwan.

This chapter consists of six parts. Section 3.1 elaborates on the potential of AI in the context of the auditing processes. The following two sections present the benefits of utilising AI applications in external auditing (3.2) and internal auditing (3.3) based on the results of empirical studies included in the literature. Then, the following two

sections describe the challenges related to the AI application in external auditing (3.4) and internal auditing (3.5). The last section concludes the chapter and highlights how AI technology will probably shape the future role of auditors.

3.1. The Potential of Artificial Intelligence in the Context of the Auditing Processes

Auditing is a methodical, independent process of gathering and assessing evidence concerning an entity's actions or assets and conveying the findings to relevant stakeholders (Mökander et al., 2023). It serves as a governance mechanism, overseeing behaviour and performance and has historically promoted procedural regularity and transparency in financial accounting and worker safety (Mökander et al., 2023). On the other hand, internal audits are impartial, objective activities aimed at enhancing an organisation's operations by evaluating and enhancing the effectiveness of risk management, control, and governance processes (IIA, 2024).

The primary goal of an audit is to collect evidence to form a valid opinion on an organisation's financial statements. The pre-planning, planning, execution, and reporting stages are pivotal. Initially, the auditor assesses reliance on the internal audit function and evaluates the entity's internal procedures and policies during pre-planning. Subsequently, risk assessment and strategy determination occur, followed by the execution of the audit assignment, which involves understanding the client, examining transactions, and conducting interviews. Finally, the auditor conducts a closing meeting, presents the audit results, and prepares the final report (Alaba and Ghanoum, 2020). Many audit processes are structured and repeatable, making them suitable for AI and data analytics applications.

IBM defines AI as technology enabling machines to simulate human intelligence (IBM, 2024). AI encompasses Machine Learning (ML), Deep Learning (DL), Artificial Neural Networks (ANN), Natural Language Processing (NLP), and Expert Systems (ES). ML facilitates automated learning from historical data, while DL allows for better predictive performance through textual analysis. Neural networks mimic human brain connections, aiding handwriting and facial recognition tasks. NLP analyses unstructured text, and ES assist in problem-solving (Hasan, 2022).

The digital age has transformed business processes, with global enterprises operating based on the Internet and platforms. Blockchain, considered the fifth pillar of the IT revolution, combines with AI to enhance data confidence and automate assurance. Robotic Process Automation (RPA) automates rule-based tasks, complementing AI (Han et al., 2023; Zemánková, 2019).

Technology plays an increasingly crucial role in auditing. When examining the benefits of using AI in auditing, it is essential to distinguish between the benefits of the use of AI in external auditing and internal auditing.

3.2. Benefits of Utilising AI Applications in External Auditing

Many studies have examined the benefits of AI applications in external auditing. We have reviewed literature reviews on this topic to ensure a complete state of the art (Table 3.1).

As seen from literature reviews, the benefits range from increased knowledge and reduced manual work to better client-audit relationships and accelerated sales. However, most studies reported increased audit efficiency, effectiveness, and decision-making capabilities.

Table 3.1. Literature reviews on the benefits of utilising AI applications in external auditing

Authors	Almufadda and Almezeini (2022)	Han et al. (2023)	Huson et al. (2023)	Mugwira (2022)	Omoteso (2012)
Sample	60 papers (2016-2020)	179 papers (2017-2019)	328 papers (2017-2022)	236 papers (1990-2019)	44 papers (1983-2008)
Main benefits:					
Increased knowledge		☑			☑
Reduced manual work		☑	☑		
Improved communications				☑	☑
Enhanced efficiency	☑	☑	☑	☑	☑
More time for complex tasks	☑			☑	
Increased productivity		☑	☑		
Increased decision-making capabilities	☑	☑	☑	☑	
Improved effectiveness	☑	☑	☑	☑	☑
Improved risk assessment		☑	☑		
Better audit quality	☑	☑		☑	
Enhanced confidence		☑	☑		
Better client-audit relationship				☑	
Accelerated sales			☑		

Source: own presentation.

Early studies suggested that expert systems can increase auditors' understanding of task processes and, in general, knowledge and knowledge transferability (Omoteso, 2012). The application of AI in external auditing increased auditors' in--depth knowledge (Munoko et al., 2020), enhanced staff training (Elliott et al., 1985), expertise development for novices and shorter decision time (Eining and Dorr, 1991).

There is much theoretical and empirical evidence that automating audit operations enabled the implementation of new audit models (Fedyk et al., 2022)

and reduced manual work (Hashid and Almaqtari, 2024; Hayes and Boritz, 2021; Holmes and Douglass, 2022) in particular, lower-level tasks (Fedyk et al., 2022). For example, blockchain and continuous auditing enabled the automated extraction of unstructured data and the preparation of that data for use in data analytics (Darwish et al., 2019; Schmitz and Leoni, 2019). ML can evaluate reporting quality and audit quality by classifying restatements in a more consistent, replicable, and scalable way than manual classification (Hayes and Boritz, 2021). Prediction models based on data mining techniques helped auditors in the review of their audit work or the work of their peers (Saeedi, 2021). Data analytics improved auditor communications (Brown and Murphy, 1990; Fedyk et al., 2022).

Audit efficiency can be understood as "the use of fewer inputs to obtain a given output." (Bamber et al., 1993, p. 2). Auditors that improve labour efficiency (Bierstaker et al., 2014; Fedyk et al., 2022; Hashid and Almaqtari, 2024; Kokina et al., 2017; Lavinia--Mihaela, 2019; Tarek et al., 2017) use AI to perform faster, less tedious and time-consuming data analysis (Hayes and Boritz, 2021; Lavinia-Mihaela, 2019; Munoko et al., 2020) and data extraction (Fedyk et al., 2022), enhance resource allocation (Hashid and Almaqtari, 2024) and spread their workload throughout the year, not only at the end of the financial cycle or during the audit process (Elommal and Manita, 2022). As a result of fewer working hours needed to produce the same output, these working hours are shorter (Elommal and Manita, 2022; Greenman, 2017; Kaya et al., 2019; Lavinia-Mihaela, 2019; Moffitt et al., 2018; Munoko et al., 2020), whereas audit workforce (Fedyk et al., 2022), and personnel costs (Fedyk et al., 2022; Tarek et al., 2017) are reduced. Ultimately, auditors use AI to save and increase profitability.

Instead of reducing employment, some companies asked auditors to take on more complex tasks (Fedyk et al., 2022; Greenman, 2017; Holmes and Douglass, 2022; Kaya et al., 2019; Moffitt et al., 2018;), focus on high-risk areas and handle a larger volume of tasks in order to increase their productivity (Fedyk et al., 2022). AI-enhanced auditors' ability to manoeuvre around massive amounts of data (Hashid and Almaqtari, 2024; Yoon et al., 2015), analyse the data (Kaya et al., 2019; Munoko et al., 2020; Hashid and Almaqtari, 2024) and gather sufficient audit evidence to base their audit opinion on (Yoon et al., 2015). Similarly, blockchain and continuous auditing allow the collect more evidence than is provided in a traditional audit while maintaining the confidentiality and security of their data, which makes these tasks easier (Elommal and Manita, 2022; Vincent et al., 2020) and together with DL, ML and NLP, improved auditors' professional judgment (Kaya et al., 2019) and decision-making capabilities (Hashid and Almaqtari, 2024; Munoko et al., 2020).

Effectiveness measures the extent to which an audit achieves its goals and objectives. Murthy et al. (2023) measured audit effectiveness using abnormal accruals, financial reporting opacity, incorrect internal control weaknesses reporting, and restatements. Several studies argued that AI application in external auditing in general improved or can improve its effectiveness (Abdolmohammadi and Usoff,

2001; Appelbaum et al., 2017; Bierstaker et al., 2001; Curtis and Payne, 2008; Tarek et al., 2017), but other studies related to the benefits of specific areas of AI. Neural networks and data analytics enhanced auditors' ability to predict and uncover fraud and misstatements in financial statements (Fedyk et al., 2022; Omoteso, 2012). Big Data Analysis and DL techniques improved insights from auditors (Alles and Gray, 2016; Earley, 2015; Hashid and Almaqtari, 2024; Salijeni et al., 2019). ML and Big Data Analysis enhance auditors' ability to detect patterns (Darwish et al., 2019), subtleties that humans would miss (Han et al., 2023), uncover hidden trends (Pan and Zhang, 2021), anomalies in data sets (Yoon et al., 2015), fraud (Munoko et al., 2020) and provide predictive insights (Pan and Zhang, 2021).

While data analytics can improve the auditor's understanding of the client operations (Fedyk et al., 2022), ML and NLP can help an organisation identify emerging threats and hazards (Hunt et al., 2022), improve auditor's risk assessment (Darwish et al., 2019; Han et al., 2023; Hashid and Almaqtari, 2024), and enable him to act proactively Kaya et al (2019) and mitigate risks (Pan and Zhang, 2021).

Audit quality is delivering useful audit reports, satisfying clients, fostering confidence in using the audit results, and enhancing audit quality (Sujana et al., 2023). Several studies suggested that audit quality increases with the application of AI (Fedyk et al., 2022; Hashid and Almaqtari, 2024; Lavinia-Mihaela, 2019) or big data analysis (Brown-Liburd et al., 2015; Cao et al., 2015; Vasarhelyi et al., 2015; Yoon et al., 2015). Some studies argued that using AI with blockchain in external auditing can lead to reduced risk of errors in lower-level tasks (Holmes and Douglass, 2022), a lower error rate (Hashid and Almaqtari, 2024; Lavinia-Mihaela, 2019; Kokina et al., 2017), lower incidence of restatements, material restatements, restatements related to accruals and revenue recognition, and restatement-related SEC investigations (Fedyk et al., 2022). Other studies reported increased data accuracy (Hashid and Almaqtari, 2024; Munoko et al., 2020;), decision consistency (Brown and Murphy, 1990; Hayes and Boritz, 2021) and better client service (Hashid and Almaqtari, 2024; Munoko et al., 2020). Cuomo (2020) argued that utilising blockchain in external auditing increases trust and confidence in AI-based processes by enriching trust in their data, models, and analytics. There is some evidence that AI application in external auditing increased auditors' confidence in their work products (Tarek et al., 2017), improved client-audit relationships (Earley, 2015) and accelerated sales (Tarek et al., 2017).

The latest studies published between 2021 and 2024 mainly suggested the same benefits of AI applications in external auditing as those listed in the literature reviews. However, the focus of the latest research has changed. Most studies reported such benefits as reduced manual work, enhanced efficiency, better audit quality, improved risk assessment, more time for complex tasks and increased audit effectiveness (Table 3.2). Interestingly, one new benefit was identified, which was not reported in the previous studies.

Table 3.2. Benefits of utilising AI applications in external auditing in light of the research studies published between 2021 and 2024

Benefits	Fedyk et al. (2022)	Hashid and Almaqtari (2024)	Hayes and Boritz (2021)	Holmes and Douglass (2022)	Hunt et al. (2022)	Liu et al. (2022)	Saeedi (2021)	Zhang et al. (2022)
Reduced manual work	☑	☑	☑	☑		☑	☑	☑
Improved communications	☑							
Enhanced efficiency	☑	☑	☑					☑
More time for complex tasks	☑	☑		☑				☑
Increased productivity	☑	☑						
Improved effectiveness	☑	☑						☑
Improved risk assessment	☑	☑			☑		☑	
Better audit quality	☑	☑	☑	☑				
Better audit fee decisions	☑				☑			

Source: own presentation.

AI application in external auditing can help auditors make better audit fee decisions. On the one hand, Fedyk et al. (2022) reported that AI application enables auditors to reduce audit fees. On the other hand, Hunt et al. (2022) provided evidence that auditors used ML to improve client risk assessment and refuse to accept risky clients, refuse to continue with a risky client, or charge higher audit fees to compensate for the more risky clients.

3.3. Benefits of Utilising AI Applications in Internal Auditing

As P. Miszczuk and P. Bednarek highlight in Chapter 2, AI can have numerous applications in internal auditing. However, to date, there is little empirical evidence that the use of AI in internal auditing has delivered significant benefits. Theoretically, AI can help internal auditors create value for the organisation by increasing the quality and efficiency of the audit process itself. These benefits are evidenced by the opinions of practitioners who believe that AI can contribute to quicker identification of areas of risk and help the organisation recognise emerging risks and threats they have yet to

consider. As a result, internal auditors can provide actionable information to reduce risk and simplify procedures (Kroll, 2021; Patil et al., 2023).

AI can help perform analytical procedures and determine where to dig deeper into transactions that appear out of the ordinary, help find and understand patterns and anomalies in data sets, and detect subtleties that humans would miss (Kroll, 2021; Patil et al., 2023). This insight allows internal auditors to refocus their test plan on high-risk areas.

Moreover, faster execution of internal audit tasks, thanks to the automation of some audit processes, would enable internal auditors to concentrate on complex tasks. For example, the extraction of unstructured data and preparation of that data for use in data analytics can be automated (Kroll, 2021; Patil et al., 2023).

Another perceived benefit of AI is its ability to streamline processes. AI solutions can automatically review transactions as they are happening and flag those that violate preset rules. This solution can be faster and provide more evidence than provided by the finance team reviewing some portion of the transactions (Kroll, 2021).

Eulerich et al. (2023) provide evidence that internal auditors perceive technology--based audit techniques (TBATs) as increasing the efficiency and effectiveness of audit tasks. Their study suggests that an increase in the use of TBATs is associated with completing more audits, finding more risk factors, providing more recommendations, and decreasing audit days.

Moreover, TBATs are often used by internal auditors for continuous auditing (Eulerich et al., 2023), which can bring many benefits to the organisation. It reduces risks, diminishes fraud attempts, facilitates the objectives of internal control, allows timely access to information, integrates internal and external stakeholders and helps external auditing, allows timely adjustments, and modifies auditors' routine tasks, thereby allowing them to focus on more critical responsibilities (Marques and Santos, 2017). Moreover, it increases confidence in transactions, operational processes, decision-making, and financial statements (Marques and Santos, 2017).

3.4. Challenges Related to the AI Application in External Auditing

A challenge is "something that needs great mental or physical effort to be done successfully and therefore tests a person's ability" (Cambridge Dictionary). Due to the varied scope of AI applications within the auditing profession, challenges encountered by external and internal auditors are addressed individually.

Despite the widely acknowledged benefits of IT-related audit methods, particular auditors encounter difficulties executing technology-enabled audit tasks with expertise. This challenge emphasises the importance of auditors improving their technological skills and closing the divide in effectively utilising analytics during audits (Dutta et al., 2022). Although human expertise is crucial for fostering innovation, productivity, and competitiveness within organisations, auditors face numerous

challenges as they strive for technology-driven auditing (Arena and Jeppesen, 2016). These challenges include (Mahapatro, 2022):

- staying updated with evolving technologies and addressing information security risks,
- overcoming limitations in qualified human resources and skills,
- establishing robust reporting structures for the IT audit function,
- ensuring adequate IT infrastructure,
- aligning technology with organisational performance,
- developing comprehensive audit methodologies for IT risk assessment and
- acquiring a deep knowledge of technological techniques in data analytics.

To effectively incorporate these technologies into auditing procedures, addressing obstacles like reluctance to change, organisational culture, and the high expenses associated with technology is essential. It is imperative to devise strategies to cultivate a culture of innovation, offer training and resources to tackle skill deficiencies and investigate cost-efficient methods for technology integration (Huson et al., 2023).

Predictions on the future role of an auditor vary with time horizon. No cognitive technologies are yet capable of self-aware intelligence (Kokina and Davenport, 2017). It is expected that in the next twenty years, routine, low-level audit tasks, such as requesting evidence from clients and documenting such evidence, will be transformed into AI tasks. AI technologies may communicate directly on both the auditor and client side (Munoko et al., 2020). Technology will likely enhance rather than entirely automate accounting processes because AI displaces specific tasks rather than entire occupations, reducing human employment (Kokina and Davenport, 2017). Future responsibilities for accountants might involve collaborating with AI to monitor its effectiveness and results, overseeing AI systems, assisting firms in the development or maintenance of new AI technologies, and handling tasks that are infrequent and thus deemed inefficient to automate with AI (Kokina and Davenport, 2017). However, AI will undoubtedly maintain the trend of acting autonomously to automate the decision-making process without any human intervention (Munoko et al., 2020; Kokina and Davenport, 2017).

Fedyk et al. (2022) explored the employment of AI workers in audit firms from the 36 largest audit firms in the US. They discovered that the main barrier to the widespread adoption of AI is onboarding and training skilled human capital. Their study results showed that significant efforts are made to overcome these challenges by investing in employee upskilling. On the other hand, Fedyk et al. (2022) argued that partners of audit firms benefit from increased product quality, greater efficiency, and reductions in personnel costs. However, junior employees may suffer from the displacement observed several years after AI investments.

Holmes and Douglass (2022) highlight the difficulties in adequately preparing graduates for a swiftly evolving audit profession. Their survey findings indicate that industry and public accountants prioritise skills such as data management, data

cleansing, and rectifying inaccurate or incomplete data, which are not as emphasised by accounting educators. Accounting programs must address this challenge by ensuring students can adapt as lifelong learners in accounting, keeping pace with the profession's transformations.

Based on 44 extensive interviews with auditors, regulators, and emerging AI software providers, Samiolo and Spence (2023) challenge the prevailing notion regarding technological shifts in auditing. This notion suggests that seemingly straightforward, basic technical tasks involve minimal judgment and are thus suitable for automation. Samiolo et al. (2023) demonstrate that crucial elements of reflection, interpretation, and critical thinking, which are arguably vital for the professional development of early-career auditors, may be compromised when automating tasks perceived as having low value. Conversely, more complex aspects of the audit process may benefit from technological assistance and be enhanced in various ways. However, the introduction of new technological frameworks creates uncertainties, leading to new and, as yet, unresolved challenges that demand auditors' judgment.

As over half of audit tasks necessitate varying auditor judgment and cannot be completely automated (Abdolmohammadi, 1999), audit automation should encompass attended automation, where auditors collaborate with and interact with automation processes. Zhang et al. (2022) utilise the Design Science Research approach and introduce an Attended Process Automation (APA) framework designed to facilitate the integration of attended automation into audits. The APA framework underscores the crucial role of auditors within an automated audit workflow, particularly in offering professional judgments that are currently irreplaceable by automation.

Zhang et al. (2022) emphasise that while attending RPA holds promise for delivering benefits, it also carries the risk of unintended consequences. For instance, errors or bot malfunctions in automated engagements could result in mistakes. To mitigate the likelihood of such errors, the automation process, particularly the bot itself, should undergo rigorous testing for faults and malfunctions before deployment and be subject to regular post-deployment review and monitoring. Furthermore, as part of the attended automation process and in line with standard auditing practices, auditors should verify the reliability and reasonableness of results produced by automated activities. Comprehensive documentation of bots is essential, as it can elucidate the bot's purpose, functionality, and governance, meeting quality and reliability standards set by management and regulators. The authors also suggest using a "meta-bot" configured to aid auditors in reviewing activities, automatically monitoring and auditing the bots assisting the auditor (Zhang et al., 2022).

Similarly, Lombardi et al. (2023) suggest that developers of AI systems must integrate preventive measures, audit firms exert essential governance over these systems, and auditors, alongside other stakeholders, should be aware of AI's limitations. The true challenge with AI lies less in its technical aspects and more

in its philosophical implications, rooted in human nature (Vanian, 2018). AI itself is not inherently biased. However, it tends to replicate existing biases present in the data used for its training (Dickson, 2018).

3.5. Challenges Related to the AI Application in Internal Auditing

Although some practitioners argue that AI can benefit internal audit functions, recent studies indicate that it is not commonly used in practice (Eulerich et al., 2023; Kroll, 2021;). There are several challenges related to applying AI in internal auditing.

Chief audit executives perceive it to be costly because they suggest that an increase in the use of AI is associated with an increase in the size of the internal audit function. Moreover, a sound AI system needs an infrastructure that can be updated regularly according to changes in data. On the other hand, organisations have difficulties in quantifying the benefits of AI applications and observing the benefits promptly (Eulerich et al., 2023; Kroll, 2021). Ultimately, internal audit functions face the challenge of gaining corporate backing and funds for AI implementation while competing with other initiatives (Kroll, 2021).

Another challenge is related to practitioners' concerns about their employment. Some internal auditors fear that implementing AI solutions in the company would deprive them of their jobs (Kroll, 2021). However, there are reasons to think human auditors will still be needed. Continues auditing, for example, may challenge human agency by transferring part of auditing to machines. However, it may also free human capacity to conduct higher-level auditing tasks (Mikkinen et al., 2022).

AI will likely change the internal audit profession (Kroll, 2021). Using AI solutions requires skills not commonly applied during internal audits, such as statistical analysis and data management (Patil et al., 2023). Moreover, AI users, including internal auditors, must be familiar with data science and aware of assumptions and application methods (Kroll, 2021). Thus, internal auditors face the challenge of acquiring new knowledge and skills. At the same time, chief audit executives are concerned with the difficulty of finding and hiring auditors with appropriate skills shortly (Eulerich et al., 2023).

AI's growing capabilities and applications pose new risks and potential harms for individuals and societies, including issues like lack of transparency, accountability, and biases against certain groups (Dignum, 2020). For example, "models used to determine which homebuyers qualify for a mortgage can, if not developed appropriately, screen out minorities who should qualify" (Kroll, 2021). These challenges highlight the crucial need for standards and ethical principles for developing and using AI at various levels – within organisations, across organisations, and within society (Kroll, 2021; Minkkinen et al., 2022).

On the one hand, continuous auditing of AI is advocated to address these risks by establishing criteria for AI systems and their usage and implementing necessary controls (Minkkinen et al., 2022). On the other hand, Vasarhelyi et al. (2004) raise

concerns about independence in the technology-assisted continuous audit since the auditor functionally becomes part of the company's internal controls by discovering issues in real-time. Tse (2020) notes that AI technology is susceptible to biases from data inputs that could lead to skewed results.

3.6. Conclusions

This chapter seeks to answer the research question on the benefits and challenges of using AI in external and internal auditing based on empirical research conducted over the last four years. A literature review revealed that using AI in auditing can bring many benefits that depend on the type of audit, function of the audit firm and time horizon.

There is a consensus that AI supports auditors in making decisions, automating repetitive activities, and learning from vast amounts of data, thus increasing the efficiency, effectiveness, and quality of external auditing. As a result, productivity increases or employment costs decrease. On the other hand, better customer risk analysis and adequate pricing decisions contribute to improved auditor-auditee relationships and increased sales volume and profitability. In the longer term, audit firms' profits should increase.

In internal auditing, theoretically, AI can add value by increasing the effectiveness and efficiency of the audit process. However, to date, only one empirical study has provided some evidence to support this hypothesis.

In order to achieve the expected benefits, internal and external auditors, audit firms, and universities face many challenges in implementing AI in auditing. Audit companies' main challenge is encouraging auditors to improve their technological qualifications and change how they work. Another challenge is to employ new auditors with appropriate qualifications due to the limited number of specialists in this field in the labour market. In turn, for universities, the challenge is adequately preparing graduates for the rapidly changing audit profession. In addition, the challenge for audit firms is to ensure appropriate control measures over the development of AI systems in organisations to reduce the risk of errors and abuses and to ensure appropriate professional development of junior auditors.

Internal auditors have noticed similar challenges related to the implementation of AI. However, due to the specificity of the internal audit function, there are several additional challenges related to the implementation of AI in internal auditing. These include the difficulty in measuring the benefits of using AI in internal auditing, obtaining corporate support and funding for this purpose, and ensuring the independence responsible for continuous AI auditing of the internal audit function.

Implementing AI in auditing in the short term involves capital expenditure for audit firms or organisations employing internal auditors. However, the long-term positive effects should outweigh the costs incurred. In the long term, audit firms should achieve higher profits due to increased productivity, more significant

revenues from the sale of audit services and increased customer satisfaction. Senior auditors should be happy to reduce the amount of tedious, routine activities to perform more complex tasks that create more excellent value for the organisation.

In conclusion, the successful integration of AI into auditing practices hinges on the ability of auditors and auditing firms to navigate the challenges posed by technological innovation while upholding the highest standards of professional excellence and ethical conduct. By embracing innovation, fostering collaboration, and prioritising ethical considerations, auditors can harness the transformative power of AI to enhance audit quality, efficiency, and effectiveness in the digital age. Future research should focus on developing more accurate methods to measure the benefits of AI in internal auditing. It is also essential to develop new standards and ethical principles supporting the development of AI in the audit profession.

As this study was based on articles published in English in the top 25 journals ranked on BYU Accounting Ranking between 2021 and April 2024, these choices constitute the limitations of this study. In the future, it may be possible to systematise existing research on this topic, which has also been published in previous years in other scientific journals and languages.

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Chapter 4

Artificial Intelligence and Attestation of Sustainability Reports. How Can Artificial Intelligence Tools be Used for the Assurance Process of Sustainability Reports?

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Climate change is a global challenge that significantly impacts our society and has increased pressure on firms to report on environmental, social and governance (ESG) factors (Bui et al., 2021). The reporting on ESG factors is a valuable source of information for stakeholders because it deals with legitimacy and institutional pressures (Maroun, 2022). Therefore, to satisfy stakeholders, the firms buy ESG assurance to represent the high quality of their reporting practices. Moreover, ESG assurance is used to enhance the reliability of sustainability and integrated

reporting to increase the quality of disclosures (Maroun, 2019). However, to draft such reports per standard-setting bodies' norms, adopting some key performance indicators and artificial intelligence (AI) tools is required (Di Vaio et al., 2020a; Polignano et al., 2022). The increasing awareness of ESG issues, shortage of natural resources, and climate change have transformed the activities of firms in innovative ways (Kolk and Van Tulder, 2010). This innovation makes the firms responsible for clear and transparent communication with their stakeholders. The literature also argues that sustainability reports significantly impact stakeholders' decision--making (Barrett, 2005). The Global Reporting Initiative (GRI) is commonly used as a standard-setting body to provide firms with specific reporting standards (Borglund et al., 2010; Brown et al., 2009).

Regardless of the importance of sustainability reports, the stakeholders are more concerned and raise questions about the integrity and transparency of the provided information. In literature, the concept of sustainability reporting depends upon two concepts: first, a methodology to focus on environmental and social issues and second, the non-financial disclosures (NFD) based on an agenda of socio-environmental choices (Di Vaio et al., 2020b). To provide transparent disclosures, the firms started to use external assurance services to improve their reliability (Kang and Kim, 2022). The external independent assurance of sustainability reporting started in 1997--1998 (O'Dwyer and Owen, 2005). There are two renowned frameworks for assurance services, i.e. in March 2003, the AA1000 Assurance Standard (AA1000AS) that was hurled by AccountAbility (Accountability, 2011) and the International Audit Assurance Standards Board (IAASB) 's International Standard on Assurance Engagements (ISAE 3000) (Junior et al., 2014). It is assumed that the assurance based on combining both frameworks provides improved results (KPMG Global Sustainability Services and AccountAbility, 2005).

The IAASB (2011, p. 19) states that it is a task where a practitioner seeks enough relevant data to draw a conclusion that will increase the confidence that users aside from the responsible party have in measuring or evaluating a subject matter against criteria. At the same time, AA1000AS defined it as an engagement wherein an assurance provider assesses and renders a judgment regarding an organisation's performance disclosures to the public, as well as its underlying systems, data, and processes, using appropriate standards and criteria to raise the information's credibility for the target audience (AccountAbility, 2008, p. 23).

Nevertheless, today, AI tools are very helpful in improving reporting efficiency, i.e. real-time accounting and reporting, continuous auditing, and attestation of reporting (Han et al., 2022). The AI tools increase the credibility of firms in terms of reporting and also enable them to play a positive role in agility (Wamba et al., 2023). Moreover, in December 2022, the Corporate Sustainability Reporting Directive (CSRD) implied a critical development regarding sustainability reporting. This Directive extends the scope of EU 2020 and demands the disclosure related to ESG indicators (Fohr et al., 2023).

This chapter aims to explore the linkage between sustainability and integrated reporting and their assurance process by analysing the existing literature. Furthermore, the chapter explores the role of AI tools in decarbonisation practices through innovation, institutional, legitimacy and stakeholder theories. More in detail, this chapter investigates how the assurance process and its tools, i.e. attestation, can guarantee the content of reports. The focus of this chapter is on a specific AI tool, ChatGPT. This chapter is more focused on AI tools regarding sustainability transition to justify institutional pressures by answering the following research questions:

RQ1: How can AI tools guarantee the content of sustainability reports about decarbonisation practices?

RQ2: How is ChatGPT the best tool for assuring and attesting sustainability reports about decarbonisation processes?

The content of the chapter is divided into the following sections: section 4.1 conceptualises AI tools, i.e. ChatGPT, ChatReport, Natural Language Processing (NLP), Machine Learning (ML), Latent Dirichlet Allocation (LDA) and assurance for sustainability reports. Section 4.2 introduces the concept of the assurance process of sustainability reports regarding AI tools under the lens of innovation, institutional, legitimacy and stakeholder theories. Section 4.3 describes the link of AI to decarbonisation practices and attestation of sustainability and integrated reporting. Section 4.4 presents a conceptual framework of sustainability reports and decarbonisation practices from the perspective of AI tools. Finally, section 4.5 concludes the study with some limitations and directions for future research.

4.1. Artificial Intelligence Tools and Assurance for Sustainability Reports

GRI defines sustainability reporting as public reporting by an organisation on its effects on the economy, environment, and/or society and, consequently, its contributions, whether favourable or unfavourable, to the cause of sustainable development (Singhania and Chadha, 2023). Therefore, the firms produce annual sustainability reports to disclose their sustainability strategies and practices (Kang and Kim, 2022). However, the question is, do the firms appropriately express their actions? That is why the assurance of sustainability reports is required. In this regard, AI tools, specifically ChatGPT, can help regulators and other stakeholders analyse the content of sustainability reports more accurately (de Villiers, 2024; SDG Compass, 2015).

AI tools have been used to prepare sustainability reports, provide assurance, and analyse large volumes of data. On the one hand, where the need for sustainability reporting arises, the chance of greenwashing adoption is also increasing (de Villiers, 2024). Advanced AI technology can help firms manage reporting according to ESG frameworks to respond to these issues (Howard-Cooper, 2023).

Employees, investors, customers, and regulatory bodies, as the firms' stakeholders, are all concerned with the sustainability reporting of firms. They are keenly interested in firms' ESG performance (Semuninx et al., 2020). In 2005, the KPMG introduced a three-step method for transparent carbon disclosure, i.e. recognition of materiality and measures of data, carbon emissions disclosure and the demonstration of steps that they are taking to achieve climate goals (Tiwari and Khan, 2020). This detailed framework requires technology adoption and capabilities as they form evolving and innovative ways in a dynamic market (Wang and Xu, 2013).

ChatGPT and Assurance of Sustainability Reports

The AI tools, specifically ChatGPT, have influenced firms by advancing accounting, finance, and traditional reporting practices. It can help the firms by offering financial advice, investment strategies, fraud detection, data entry and report generation (Rane, 2023a). ChatGPT adoption must be aligned with firms' digitalisation capabilities and strategies to achieve better results (Eulerich and Wood, 2023). The ChatGPT showcases advanced capabilities in decarbonisation practices, i.e. sustainability reporting and renewable energy resources. It aids the firms in reporting assurance, revising strategies, and improving their performance, and the cycle continues (Rane, 2023b). Apart from its benefits, ChatGPT also faces reliability-related challenges in reporting analysis. Despite being sensitive, it may misinterpret financial statements that lead towards flawed conclusions (Zhao et al., 2023). Combined efforts from AI tool developers, regulatory bodies, and financial experts are required to address these challenges (Shen et al., 2023). Their collective efforts will accurately tackle these issues and improve firms' efficiency and performance (Rane, 2023a).

ChatReport and Assurance of Sustainability Reports

The AI launched a new tool called ChatReport, a generative source to interpret information by allowing users to access the quality of climate disclosure in sustainability reports (Human, 2023). Unlike ChatGPT, ChatReport is linked only with the information retrieved by the users. It automatically analyses the reports based on recommendations of the Task Force on Climate-related Financial Disclosures (TCFD) (Ni et al., 2023). It works in four modules:

i. Report Embedding: It divides the sustainability report into informative textual parts and transforms it into a vector space representation.
ii. Report Summarisation: It summarises the report based on recommendations of TCFD by retrieving the relevant information from the report so that it can be read efficiently.
iii. TCFD Conformity Assessment: It analyses to what extent the report is based on TCFD recommendations.
iv. Customised Question Answering: It enables the users to pose specific questions.

Apart from the importance of ChatReport, its outputs must be used for references, not as evidence. As it wholly depends upon the information provided by the firms in their reports, that is its limitation (Ni et al., 2023).

Natural Language Processing and Assurance of Sustainability Reports

NLP deals with the interpretation of data in written or spoken language, as well as natural or human language. The scientists and programmers working in the field of NLP design such programs that can understand human language and, in response, can summarise it in a more elaborate form (Howard-Cooper, 2023). NLP is considered the best AI tool for generating insights from unstructured data sources regarding sustainability reports. It is assumed that up to 90% of the globally generated data is unstructured, and the most commonly unstandardised form of data is sustainable finance data. For transparent reporting, the unstructured sustainability data must be sorted for institutions and stakeholders; for this reason, NLP plays a target role in such issues. The NLP tool is used in meta-analysis and climate disclosure analysis to detect facts related to climate change (Webersinke et al., 2021). It helps the analysts retrieve helpful data for their future decision-making.

Machine Learning and Assurance of Sustainability Reports

ML is recognised for its potential impacts on greenwashing; a tactic companies often use to manipulate sustainability reporting. In recent years, ML has significantly advanced the accuracy and transparency of sustainability reporting, helping to mitigate deceptive practices (Goodell et al., 2021). The ML algorithms can analyse disclosures by measuring the readability of sustainability reports (Ning et al., 2021). It is easier to recognise different patterns that lead to effective managerial decisions (Goodell et al., 2021). The combination of ML and NLP can assess the complex information in sustainability reporting by proposing different methods to detect non--compliance to corporate social responsibility (CSR) (Kotzian, 2021).

Moreover, analysing text and data in large quantities is helpful faster than manual analysis and review (Yim et al., 2016). It encourages the stakeholders to consider the negative impact of greenwashing in disclosures (Moodaley and Telukdarie, 2022). ML is considered a comprehensive AI tool that has been perceived to have increased usefulness by researchers and scholars (Moodaley and Telukdarie, 2022).

Latent Dirichlet Allocation and Assurance of Sustainability Reports

Integrated reporting focuses on financial and governance details, while sustainability reporting emphasises environmental and social aspects (Sick, 2022). Firms disclose sustainability practices to engage stakeholders effectively, and it is crucial for these reports to represent sustainable practices authentically. To analyse voluntary sustainability disclosures, LDA is utilised to summarise the entire report's content (Ning et al., 2021). The reports can be identified using LDA as environmental

performance, social engagement and governance. By using these factors in sustainability reporting, the firms manage their social reputation to attain societal acceptance. In this regard, LDA enables stakeholders to check the efforts made by labourers in the category of social engagement (Ning et al., 2021). The application of LDA is tempting and requires little assistance, but users should specify the topics (Sick, 2022). In the literature, a few studies have used LDA as manual coding is needed to process documents (DiMaggio et al., 2013).

4.2. Contribution of Theories to the Assurance Process of Sustainability Reports Regarding Artificial Intelligence Tools

The ESG information presented in sustainability reports is a valuable source of information for stakeholders and regulatory bodies. These types of disclosures reduce the cost of capital by meeting investors' expectations (Maroun, 2022). Nowadays, when the concern of ESG reporting is growing, stakeholders also demand assurance. Therefore, to balance the legitimacy of institutions and stakeholders, the assurance acts as a monitoring tool to improve the quality of sustainability reports (Wang et al., 2019). Firms with good sustainability performance have greater chances to get sustainability assurance than firms with less sustainability performance (Rohani et al., 2023).

Moreover, the legitimacy theory posits that firms with a high level of legitimacy are more concerned about their actions (Datt et al., 2022), whereas the stakeholder theory makes the firms responsible for a broader range of stakeholders (Freeman, 1984). Furthermore, as per innovation theory, to deal with adopting innovative AI tools and decarbonisation practices, the institutional theory justifies that the regulatory norms design the firm's policies and practices (Datt et al., 2022). After meeting all the initial pressures of institutional and stakeholders, firms must go through the assurance process for their sustainability reports. It provides a complete picture of firms' behaviour and allows stakeholders to ensure the implementation of ESG standards in firms' reporting (SGS, 2023).

Assurance Process of Sustainability Reports regarding Artificial Intelligence Tools under Innovation Theory

In this era, where the world revolves around technology, the previous knowledge is obsolete, and innovation becomes the roadmap to success. Therefore, the firms are trying to support their strategies with innovative capacity (Bronzetti et al., 2023). The ability of firms to present the disclosure of innovation inspires stakeholders to decide in favour of firms (Bronzetti et al., 2023). Moreover, the firms that invest in innovative deeds have solid justification to disclose it in their reporting as sustainability practices to improve their relationship with stakeholders (Radu and Francoeur). Further, the reporting on ESG factors, including innovation, reduces the high uncertainty and encourages new investments in innovative activities (Dunbar et al., 2019).

The AI tools play a vital role in the assurance of sustainability reporting. The assurance tools encourage the stakeholders to discover new opportunities that can transform the firms' business models per standards-setting bodies (Van de Wetering et al., 2022).

Assurance Process of Sustainability Reports regarding Artificial Intelligence Tools under Institutional Theory

In literature, the firms' managerial capabilities regarding sustainability reporting and technology adoption always depend upon numerous regulative and normative drivers (Bebbington, 2007; Gray et al., 2010). In 2002, Adams explored that the corporate factors, i.e. profits and financial performance of firms, and contextual factors, i.e. political, legal, social, economic and stakeholders, as well as institutions, influence firms' decisions to report (Baldarelli et al., 2014). Therefore, sustainability reporting is a discretionary process from stakeholders and institutional pressures (Young and Marais, 2012). With the help of institutional theory, the firms are taking initiatives towards assurance of sustainability reporting to meet environmental concerns (Baldarelli et al., 2014). Moreover, the institutional theory posits that institutional pressures shape the corporate behaviour of firms (Matten and Moon, 2008).

The tendency is increasing daily to have voluntary assurance of sustainability reporting for the firms to achieve stakeholders' confidence (KPMG, 2013). However, due to the high costs of assurance services, many firms do not opt to ensure their sustainability practices (Hassan et al., 2020). However, to improve credibility and transparency, firms get assurance to keep their stakeholders aware of their actions on ESG issues (Clarkson et al., 2011). Meanwhile, with the development of technology, AI tools can aid in sustainable efforts by increasing security and transparency in reporting. Also, the regulators, employees, accounting professionals and users must be aware of technological skills (Hassan et al., 2020).

Assurance Process of Sustainability Reports regarding Artificial Intelligence Tools under Legitimacy Theory

Reporting ESG factors improves firms' strategies and routine practices committed to social and environmental impacts (Pitrakkos and Maroun, 2020). Due to the increasing concerns of stakeholders, not only for mandatory disclosures but for voluntary assurance to enhance the firms' legitimacy by reducing asymmetry information (Rohani et al., 2023). Moreover, to meet the institutional pressures and stakeholders' demands, NFD and its assurance worked as a legitimation strategy (Kuruppu and Milne, 2010). From a legitimacy perspective, the firms' practices and reporting must be aligned with the norms of the society in which they operate (Rohani et al., 2023).

The new institutionalism restructures the firms to adopt digitalisation towards sustainability transition (Schiavi et al., 2023). Firms initially adopt this perspective to reduce uncertainties in their actions (Greenwood et al., 2002). Then, on the next

level, the institutional pressures reform the firms to undergo technological change in their reporting practices (Hinings et al., 2018). This new perspective wholly depends on technological adoption in terms of choice to meet environmental pressures and ensure stakeholders' legitimacy (Currie, 2011).

Assurance Process of Sustainability Reports regarding Artificial Intelligence Tools under Stakeholder Theory

The stakeholder theory links a firm and its stakeholders (Freeman, 1984). Unlike the legitimacy theory, the stakeholder theory is a detailed managerial act to report on ESG factors (Singhania and Chadha, 2023). Applying this perspective in the firms regarding assurance of ESG factors creates a trustworthy relationship with stakeholders (Datt et al., 2022). The AI tools help verify that the firms meet the criteria of standards-setting bodies in their sustainability reporting. The assurance assessment supports the firms in the following ways:

- managing ESG factors,
- assuring ESG targets,
- managing internal controls,
- verifying NFD,
- recommending improvements in disclosures.

AI tools can provide accuracy in diversified languages. Therefore, adopting AI tools for the assurance process of sustainability reports is gaining increasing trustworthiness of stakeholders (Freeman et al., 2021).

4.3. Artificial Intelligence for the Decarbonisation Practices: Attestation, Sustainability Reporting and Integrated Reporting

The depletion of natural resources raises global issues, and decarbonisation practices with digitalisation are the best solution to these environmental problems. Through AI-advanced technologies, decarbonisation practices can support carbon neutrality goals for a sustainable transition (Kurniawan et al., 2023). AI can contribute towards sustainable development goals by addressing the issues, i.e. climate change, sustainability reporting, sustainable business models, and transparency in sustainability practices (Jelinek et al., 2023). Adopting AI for decarbonisation practices employed by firms can improve their environmental performance and transparency in sustainability reporting (Wamba et al., 2023). AI can also make significant changes to adopt decarbonisation practices as they can increase efficiency in routine activities (Noori et al., 2023).

Furthermore, the digital transformation of green technological innovation is the primary driver of decarbonisation (Kurniawan et al., 2023). Therefore, decarbonisation is the priority goal and a challenging global issue. The complete transformation of

existing technology with green energy resources is the distinctive feature on which firms are putting their efforts (Vorozheykina, 2022).

Moreover, to standardise the operations of firms, which also includes the assurance and attestation of sustainability practices in reporting, GRI guidelines are considered as best because do not only focus on the production of sustainability reports but also demand external independent auditors to evaluate the reports prepared by firms (TUV SÜD, n.d.). The report further explains that the firms can achieve multiple benefits from verification of reporting, i.e. accuracy and comparability of data, improvement, and trustworthy relations with stakeholders. Meanwhile, AI tools encourage firms to use a systematic approach and integrated management for decarbonisation practices to develop technological innovations towards sustainability transition (Vorozheykina, 2022). It is proposed that the contribution of AI to decarbonisation practices should be based on social norms. The cause-and-effect relationship of environmental development to achieve complete benefits from decarbonisation practices is still ongoing (Ragulina et al., 2022).

4.4. Conceptual Framework of Sustainability Reports and Decarbonisation Practices with Perspective of Artificial Intelligence Tools

Sustainability reporting and its assurance is an effort put forth by the firms to be accountable to their stakeholders. The number of firms producing sustainability reports has increased in the past decade (Junior et al., 2014). Furthermore, adopting AI tools with the engagement of accountants and experts regarding assurance and attestation of sustainability reports has emerged as a new practice. Therefore, ChatGPT is ultimately popular due to its capabilities regarding sustainability reports' assurance. The fact that ChatGPT is an emerging AI tool means that firms are using it to ensure the sustainability of their sustainability reports to sustain the legitimacy of stakeholders and regulatory bodies (Maroun, 2022). Sustainability reporting plays a crucial role in legitimising firms' relationships with stakeholders. Moreover, the legitimacy theory is vital in making the firm credible to stakeholders (Pitrakkos and Maroun, 2020).

The stakeholders are dependent on the information stated in firms' sustainability reports. The stakeholders and regulatory bodies are more concerned with ecological sustainability, which is only possible by adopting green technologies (Kurniawan et al., 2023). Therefore, the legitimacy theory restricts firms from operating in socially acceptable manners, whereas stakeholder theory gives preferences to specific groups that are directly linked with them. Unlike both, the institutional theory pursues sustainability disclosures as per regulatory norms (Singhania and Chadha, 2023). Collectively, all of them postulate to manage ESG reporting and its assurance. Therefore, the automatic analysis provided by AI tools empowers stakeholders to

check the firms' performance, ESG risks and opportunities to make more sustainable decisions (Ni et al., 2023). Based on these tools, the customers and employees can evaluate the performance of firms, whereas the regulatory bodies can monitor the practices of firms aligned with sustainability regulations. The conceptual framework of AI tools, specifically ChatGPT, for attestation of sustainability and integrated reports and their assurance for decarbonisation practices towards sustainability transition is shown in Figure 4.1.

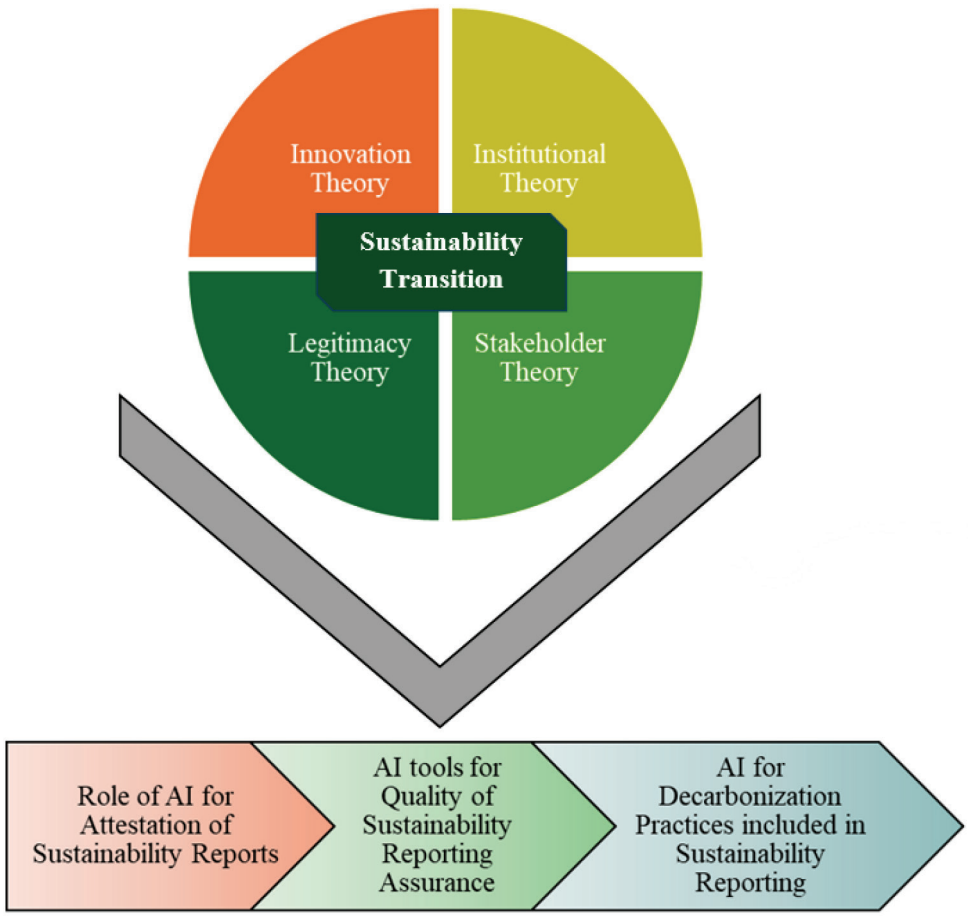

Figure 4.1. Conceptual framework "AI tools for attestation and assurance of sustainability reports and decarbonisation practices"

Source: own presentation.

4.5. Discussion and Conclusions

Concerning our RQ1, "How can AI tools guarantee the content of sustainability reports about decarbonisation practices?". By automating the processes of data collection, integration, and verification, AI tools improve the transparency and quality of sustainability reports on decarbonisation activities. In order to ensure data integrity, these tools employ advanced algorithms to collect data from a variety of sources, identify anomalies and cross-reference information with outside benchmarks (Nishant et al., 2020). The firms can report on the most recent data and simulate future scenarios thanks to real-time monitoring and predictive analytics, which offer continuous oversight and trend analysis (Floridi et al., 2020). Through interactive, real-time communication, ChatReport uses NLP to generate, analyse, and improve reports, making the reporting process more dynamic and approachable (Maibaum et al., 2024), while NLP guarantees clarity and adherence to regulatory norms (Tapscott and Tapscott, 2017). In addition, the quality and comprehensiveness of sustainability reports can be enhanced by ML algorithms' abilities to handle and analyse huge datasets, find patterns, spot anomalies, and forecast future trends in emissions reduction (Moodaley and Telukdarie, 2023). By introducing statistical noise to individual data points prior to analysis, LDA protects sensitive information while preserving the general usefulness of the data (Ning et al., 2021). By offering interactive data views and feedback channels, AI-driven dashboards engage stakeholders and promote openness and ongoing development (Wamba et al., 2015). Moreover, this integrated strategy promotes open and ongoing stakeholder participation while protecting data privacy and improving analytical precision.

With regard to RQ2, "How is ChatGPT the best tool for assuring and attesting sustainability reports about decarbonisation processes?". Reliable sustainability reporting depends on ChatGPT's capacity to process complex text data effectively, discover errors, validate facts, and assure adherence to reporting requirements (Sashida et al., 2023). As highlighted by Kolar in Chapter 5, ChatGPT enables firms to improve their planning and decision-making processes. Furthermore, it is consistent with the remarks of Cojocaru et al. in Chapter 6 that ChatGPT can analyse huge volumes of data to improve the dependability and accuracy of sustainability reports (Yonis Mousa, 2023) but to enhance reporting and offer insightful data, the uploaded databases need to be managed consistently, precisely, and thoroughly (De Villiers et al., 2024).

As climate change is gaining global attention, stakeholders demand a transparent view of sustainability practices. However, the average sustainability report comprises more than 70 pages, which makes it difficult for policymakers, investors, and other stakeholders to analyse it (Ni et al., 2023). Meanwhile, depending on a third party is expensive and might cause a lack of transparency. Therefore, AI tools are considered the most appropriate and transparent technique for analysing sustainability reports. AI tools can be used to generate and analyse text related to sustainability

engagements in firms. In 2020, Lee and Tajudeen (2020) explored that AI-based accounting software can increase the output and effectiveness of firms' governance.

Moreover, Lombardi and Secundo (2021) highlighted the significance of digital revolution and reporting processes. The assurance process of sustainability reports helps the stakeholders by improving organisational efficiency. AI provides an integrated solution to combine finance and NFD to increase the reliability of reports among managers and promote sustainable goals internally. However, regarding sustainability reporting, using AI tools raises some key concerns. The sustainability reporting assurance should focus on ChatGPT to support the assurance process, i.e., it helps technology streamline the analysis process and evaluate the reliability of reports.

One of the significant issues is ensuring the reliability of AI-generated reports, specifically ESG factors (de Villiers et al., 2024). Therefore, the firms are required to improve the efficiency and accuracy of information presented in reports. Meanwhile, the users must be aware of AI technology and evaluation strategies. Furthermore, the firms must have five competencies for transparent sustainability reporting and assurance systems: systems thinking, interpersonal skills, critical thinking and problem-solving, adaptability and flexibility, and technological capabilities.

Limitations of the Study

This chapter focuses on the transition to sustainability with the help of innovation, institutional, legitimacy and stakeholder theories. Regardless of the increasing concerns of stakeholders and institutional pressures regarding adopting AI tools for attestation of sustainability reports and quality of sustainability reporting assurance with the help of decarbonisation practices, it is rarely touched in the literature related to actions taken by the firms. Therefore, firms are adopting greenwashing to manipulate the picture of their performance in their reporting. To mitigate the risk of greenwashing, the firms must adopt assurance and attestation of their sustainability reports, which is quite challenging. Furthermore, adopting AI tools is not affordable for all firms because of their enormous costs. Meanwhile, firms need financial experts for such services to meet all the reporting standards. Therefore, the regulatory bodies should formulate flexible strategies that make this adoption possible for all firms in this competitive era.

Directions for Future Research

This chapter provides new innovative directions for scholars to focus on different AI tools and firms' performance regarding agency and resource-based view theories. Further research can be more precise on implementing AI tools to help firms reduce the risk of greenwashing and stakeholders get a clear picture of sustainability reporting and firms' performance. Furthermore, scholars should focus on training and awareness about using ChatGPT and other models to enable the users to understand technology. Also, decarbonisation practices regarding the adoption of renewable

energy resources should be considered from economic, technological, and social perspectives to ensure firms' reporting quality.

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Chapter 5

The Future of the Internal Audit Profession and Its Change Due to the Development of Artificial Intelligence Solutions

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What will the future of internal audit be? Will we still have an internal auditor in 10 years, or will an AI solution replace it? There is still no clear answer to this today. This research aims to analyse the thoughts on the future of internal auditing as a profession and to give some thoughts on what internal auditing will be like in 10 years, focusing on the possible impact of AI solutions on internal auditing in the next decade. We have collected thoughts from various authors and opinions from internal auditors in Slovenia.

Today, the question of what the future changes in internal audit will be and whether the internal auditor job will remain or be replaced by an AI solution has not yet been researched and answered. An important limitation of our research is that we are not exploring possible legislative changes in this area, which, like AI, could significantly change the profession and the tasks of internal auditors. We limit ourselves to looking at internal auditing in general, as no specific area/topic within this activity has been selected. The chapter assumes that internal auditing in small and large organisations, in the private and public sectors, in different industries, etc., is not the same and will not be the same in the future; due to the limitations of the research, we do not explore internal auditing from all these different perspectives.

However, taking a 10-year perspective is long enough that we can still make changes to ensure the existence of an internal audit.

The chapter consists of four parts. Section 5.1 elaborates on the future of internal auditing based on the literature review. Section 5.2 introduces the research methodology applied. Section 5.3. presents the results of the survey of Slovenian internal auditors on how they see themselves in the future and how AI will affect internal audits. The last section concludes the chapter and presents the prospects of internal audit.

5.1. Thinking about the Future of Internal Auditing: The Results of Literature Review

The future of internal audit and the internal audit profession is a hot topic of research at the moment, with AuditBoard (2023), Chambers (2024) and the Institute of Internal Auditors (IIA Global) (n.d.), which is currently undertaking a project to renew its vision for internal audit by 2035. The IIA Global project involves research, surveys and interviews with internal auditors, managers and other stakeholders to help the IIA, the professional body for internal auditors, arrive at a renewed vision for internal auditing by 2035. Preliminary findings from The IIA Global (2024) project suggest that internal audit in the future will be more strategic: focused on key risks and opportunities to move the organisation forward. Internal auditors will need to demonstrate interdisciplinary competence, using a wide range of skills and knowledge, and will be technologically up-to-date.

Some writers on the future of internal audit, e.g. Franco (2021), have argued that the evolution of the internal auditor has stalled, that the development of ethics and the link to the investigation of economic crime has been too slow and that internal audit is therefore losing ground and that it is currently facing bad times ahead. According to the World Economic Forum's report 'The Future of Jobs' of 20 October 2020, accounting and auditing rank 2nd-4th on the list of jobs that are in declining demand and could disappear in the future (World Economic Forum, 2020). Franco (2021) believes that more attention will need to be paid to scientific research on internal auditing in the future and that this should be applied to its work. Kristensen et al. (2021) argue that internal audit in the future will be based on the development of new skills and expertise and helped by introducing new technologies and approaches. Thus, it should seek strategic support from management and play a key role in changing the organisation's culture.

Internal auditing as a profession is at a crossroads (Lenz and Jeppesen, 2022). It is losing attention and relevance in its operating environment. Stakeholders now see less and less added value in internal auditors, and in the contributions of internal auditing, and at a macro level, Lenz and Jeppesen (2022) predict a threat to the legitimacy and relevance of internal auditing as a profession. The good news and

the bad news are that the future of the internal auditor is uncertain and can still be influenced. Deloitte (2018) predicted that the next generation of internal audit would be internal audit 3.0, which focuses on providing trust, advice, and foresight. This approach is more proactive and helps management manage emerging risks, technologies, innovation and disruption, with internal audit using innovative approaches and technology such as data analytics and robotic automation to deliver real-time services. For some authors, the internal audit functions may be the most suitable for implementing AI tools in continuous auditing, as Miszczuk and Bednarek highlight in Chapter 2.

In substance, the internal audit has lost focus recently, so Lenz and Jeppesen (2022) say that internal auditors should focus on five key areas of action and focus, i.e. Planet, Public, Profession, Prosperity and People. This will save the future of the internal auditor's job. These focuses mean (Lenz and Jeppesen, 2022):

Planet

No planet, no (internal) audit, and no Plan B – environment, society, and governance (ESG) are key, literally speaking, and internal audit has an important role to play in this. Internal auditors need to ask themselves critically whether internal audit has engaged satisfactorily in the ESG debate. It will be necessary to do more and better as an internal auditor for the planet. Chambers (2022, as cited in Lenz and Hoos, 2023) warned that internal auditors are unduly sidelining environmental, social and governance (ESG) risks. Internal auditors do not currently have a meaningful role as assurance providers and are absent from potential ESG advisory services – on both sides of the Atlantic. Chambers (2022, as cited in Lenz and Hoos, 2023) argues that internal auditing is suffering from the "ESG powerlessness syndrome". Similar to the animal world, the internal audit function is in a state of frozen response when it comes to ESG issues. The ESG challenge is so great, and the threats to the role of the internal audit function (IAF) are so real that the profession reacts like animals to a threat: frozen. We discuss and challenge the professional requirements of 'objectivity' and 'independence' in the context of ESG, as they may represent obstacles to the IAF playing a meaningful role in the ESG agenda. We suggest that practitioners consider broadening the repertoire of internal audit. We propose an ABC-model © of internal audit, adding "building" as a new third pillar of internal audit value creation, complementing traditional assurance and advisory services. We encourage internal auditors to become "builders" in addressing ESG challenges in their organisations. We borrow the words of Yvon Chouinard, founder of Patagonia, which is often used as a model ESG company when we suggest "Let Internal Auditors Go Surfing" as a call to action.

Public

No third-party evaluation, no (internal) audit; this means – no client – no audit, in other words. Internal auditors' self-assessments are biased and of very little value. For internal auditors to be better accepted, to be relevant and to increase their impact,

stakeholders need to see and value the service provided. Internal auditors need to be actively involved in promoting and influencing regulators as well as boards and increasing awareness and understanding of the value proposition of internal audit, as all stakeholders need to understand how internal audit differ from external audit.

Profession

No unique selling proposition, no USP, no "focal area", and no (internal) audit, after all. The internal audit profession still has no common core. With this vague value proposition, the internal audit profession is constantly at risk of over-promising, under-delivering, and being seen as a 'jack of all trades' and a 'master of none'. Internal audit needs to reduce the diversity of practice and focus on what distinguishes it from external audit, i.e. the ability of internal audit to participate in the organisation's governance processes, which external audit cannot do for reasons of independence. We also believe that internal audit needs a more compelling and sticky idea and story to tell about its remit. For this story, we suggest using a compelling metaphor, as this facilitates understanding by transferring experience from one context to another (Lakoff and Johnson, 1980, as cited in Lenz and Jeppesen, 2022). Accordingly, we propose the use of the "management gardener" metaphor to explain the value proposition of internal audit.

Prosperity

No business, no (internal) audit; an internal audit must find ways to add value to the private company or public institution it serves. Chambers (2016, as cited in Lenz and Jeppesen, 2022) says that an internal audit is more than just the brakes in a car. It is part of the navigation system. Internal audit must serve the overall strategy of the organisation and its well-being. If the organisation fails because it is not profitable, an internal audit fails too.

People

People make all the difference. People use technology. Internal auditors are not robots. Neither are their colleagues and clients. Business is about people working together.

AI has and will have a drastic impact on the future of internal auditing (Griffin, 2019). Matis (2015) wrote about what IA itself predicts for internal auditing, and he got this answer from AI about the future of internal auditing: "Over the years, the scope of internal auditors' work will continue to evolve and expand, especially in strategic and operational efforts to verify an organisation's compliance at all levels. Looking ahead, it is anticipated that internal audit will play an important advisory role, becoming an important catalyst for business development and focusing organisations on emerging risks. This transformation of the whole internal system, consisting of control and audit, which seeks to foster a risk-focused organisational

culture, is in the process of evolution but is complex, with conflicts of interest and little understanding by most companies when it comes to the introduction of such a system, as well as various credibility issues, are limiting the pace of development for the time being." This account by Matis (2015) shows an unambitious thinking about the future of internal auditing in 2015. Today, it seems that the slow pace of development is the key stumbling block in the future existence of internal auditing. Whether internal auditing is outpaced by the use of AI or the pace of development is too slow, the future of internal auditing may be badly affected.

As indicated by D. Tal (n.d.), according to Oxford report, 47% of today's jobs will disappear, mainly due to machine automation. If one watched the film Ex Machina (2014), one might have wondered whether we could really be replaced by robots in our own image and human intelligence. Whether we will one day come to work and there will be a black box or even a humanoid at our workplace. Or is this just an image in the movies, and for us, tomorrow, there is no fear that something like that could happen to us?

The future is never completely fixed, but we can always influence it to a greater or lesser extent. If we want to predict whether AI will abolish the post of internal auditor, we first need to define what that post represents. If the internal auditor is a job where tasks are repetitive deterministic process tasks, in that case, it is more likely that these tasks will be automated and replaced by AI. However, if the job is characterised by complex consultancy tasks, soft skills, experience, other complex non-repetitive (always different) tasks, and an ever-new work methodology, it is more likely that AI will not replace these tasks.

McCafferty (2023) finds that internal audit leaders are delaying critical technology investments in generative AI and automation: 75% have not yet implemented generative AI in internal audit, only 40% have a clear understanding of how AI is being used in their organisations, and a whopping 25% have identified risks or created guidelines for the use of AI. Computers and networks provide most of the information needed for auditing. To be effective, internal auditors need to use the computer and specific computer software as an audit tool, audit automated systems and data, and understand the business purposes of systems and the environment in which systems operate. Audit administration is another important use of computers and networks by auditors. By finding new ways to use computers and communications, auditors improve their ability to review systems and information and manage their activities more effectively. Automated tools, now often referred to as AI tools, enable auditors to increase the individual productivity and efficiency of the internal audit function.

The development of AI solutions will fundamentally change the internal audit profession over the next decade. Studies show a shift from routine tasks to more strategic analysis and advisory roles for auditors (Deloitte, 2018). AI is expected to dominate mundane tasks such as data collection, anomaly detection and control testing, allowing auditors to focus on higher-value activities such as interpreting results, identifying emerging risks and providing insights to improve performance

(Savage, 2023). This transition will require new skills for auditors, who must have technical knowledge of AI capabilities and strong critical thinking skills to effectively evaluate AI results and ensure overall audit quality (Savage, 2023). Auditors must adapt to new technologies and processes to do their job effectively (Rausenberger and Prenrecaj, 2017).

From a review and analysis of the writings on the future of internal audit today, there is no prediction that the internal auditor will disappear in 2033, but we note that the writers predict that the content and way of practising the profession of internal auditor will be different in the future. Therefore, in order to test amongst internal auditors what they think about their future, we put forward the following positive research hypothesis:

H1: In 10 years, the internal auditors will still exist and will still have a place and a job, but they will have to be different and do their job differently than today.

The survey will also seek to answer the question of how internal auditors themselves see their work in the future and how AI will affect internal auditing. Our survey aims to look at least 10 years into the future.

5.2. Description of the Research Design: A Survey on Internal Auditors in Slovenia

A survey on how internal auditors see themselves in the future and how AI will affect internal auditing was conducted in Slovenia. At the end of 2023, there were 506 state internal auditors in Slovenia registered in the Directory of State Internal Auditors, of which 112 were tested state internal auditors. Internal auditors in the private sector in Slovenia are organised by the Internal Auditors Section of the Slovenian Institute of Auditors, which each year devotes a few words to the state of internal auditing in Slovenia and is an integral part of the annual report on the work of the Slovenian Institute of Auditors. In this report, we can find, among other things, the information that as of 31 December 2023, 275 tested internal auditors in Slovenia held a certificate of professional title and that as of that date, 92 active tested internal auditors in Slovenia were listed in the register of active tested professional title holders. In 2018, the Slovenian chapter of the American umbrella organisation of the IIA (The Institute of Internal Auditors) also became independent and is expected to have around 267 members at the end of 2022. However, internal auditing in Slovenia also involves professionals who are not covered by any of the organisations, statistics and reports mentioned above. The current situation in the field of internal auditing in Slovenia is unclear, which does not bode well for the future of internal auditing in Slovenia. The members of these associations are the entire population of internal auditors in Slovenia covered by this survey.

Our research on the future of internal auditing is based on data collected through a questionnaire among Slovenian internal auditors, and we asked all internal auditors in Slovenia to participate. The questionnaires were sent to all tested internal auditors in Slovenia at the Slovenian Institute of Auditing (92 of them in 2024) and to all members of the Slovenian IIA Chapter (about 270 of them) at their e-mail addresses with an invitation to participate. We do not have an exact number of respondents who received the questionnaire. The questionnaire used had ten short questions and was open-ended. The questionnaire was made available on the *1ka.si* website (https://1ka.arnes.si/IA2033), and a link to it was sent with the invitation to fill in the freely accessible online form via e-mail. The survey was active between 25 February 2024 and 15 March 2024. Each respondent or e-mail address could only fill in the questionnaire once. 247 respondents clicked on the survey, and 91 internal auditors completed the survey, i.e. they were the respondents or respondents to our survey.

We were thus able to collect 91 completed and usable questionnaires. Of these, 16 men and 74 women took part, or 18% men and 81% women and 1% other gender. This is already the first figure that can be interpreted differently. Firstly, those men have a greater affinity for completing surveys than women, since among the list of tested internal auditors of the Slovenian Institute of Auditors, only 12% are male internal auditors, and in the percentage of completed surveys, they took 18%. Secondly, those male internal auditors are relatively more interested in disclosing how they envision internal audit in the future. However, this gender composition may be purely coincidental and influenced by other unknown factors. The sample of respondents among internal auditors shows that the average age of an internal auditor in Slovenia is 48.7 years, with a standard deviation of 6.78 years. The youngest internal auditor in the survey was 31 years old, and the oldest was 64 years old. On average, the respondent has 22.2 years of experience. The sample includes a respondent with 4 years of experience and one with 39 years of experience. From this point of view, we can conclude that the sample reflects well the entire population of internal auditors in Slovenia, both younger and less experienced, as well as older and more experienced internal auditors. Therefore, our survey findings are valid and can be generalised to the entire population of internal auditors in Slovenia.

The sample of questionnaires obtained also had very dispersed participation of respondents in the activity variable. Thus, the largest number of state internal auditors were from the public administration sector, accounting for 34%, followed by the banking sector with 32% and the insurance sector with 6%, with the remaining 27% belonging to the business and other activities sector. The respondents represented a variety of activities as internal auditors appear in these activities. The sample thus covers the activities well, which is an additional reason why we consider the resulting data sample to be a good and representative representation of the population of internal auditors in Slovenia. We have also verified this, and the chi-square test for the normality of the distribution confirmed our initial findings, as the actual and theoretical distributions were in good agreement.

We used content analysis, simple statistical indicators such as frequencies and proportions, and bivariate correlations to process the data.

5.3. The Future of Internal Auditors' Profession and Auditors' Tasks: Research Findings

The first question of the questionnaire was directly related to our hypothesis: "On a scale of 0-100%, how likely do you think it is that an internal auditor will still have a job in 10 years' time?".

The results collected through the survey show that the arithmetic mean of the responses of the internal auditors surveyed is 75% on a scale of 0% to 100%. On average, respondents think there is a 75% probability that an internal auditor will still have a job in 10 years' time. The standard deviation of the arithmetic mean is 27.13% (N=90). Hypothesis H1 can be accepted, which means that internal auditors in Slovenia believe that in 2033, the internal auditor will still have a position and a job. The responses received on the existence of an internal auditor as a post are shown in Figure 5.1.

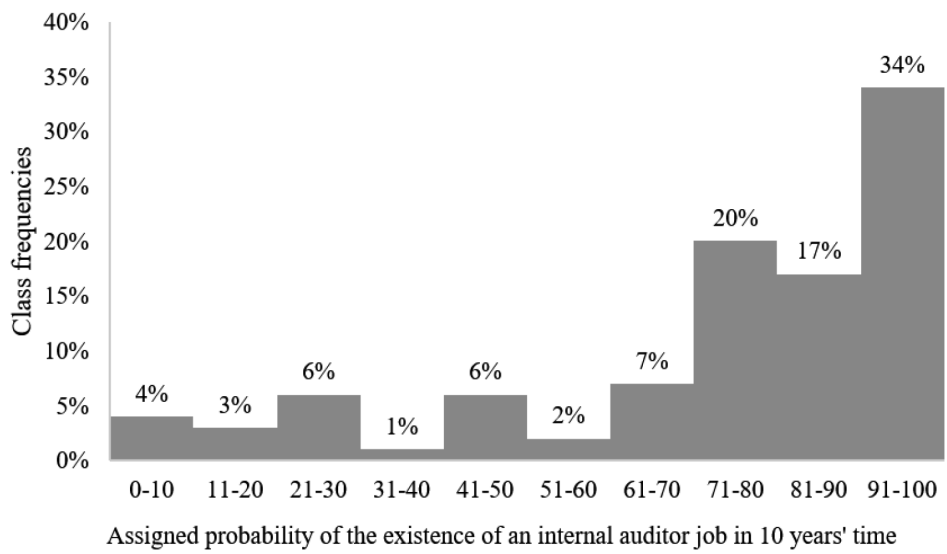

Figure 5.1. Existence of an internal auditor job in 10 years

Source: own study.

The data collected through the survey show that there are some estimates of internal auditors who think there is less than a 50% probability that the internal auditor job will still exist in 10 years' time, with 20% of all respondents giving such estimates.

The remaining 80% of respondents predict that there is at least a 50% probability or more that the internal auditor job will still exist in 10 years' time. The estimate of 100% probability that the job of the internal auditor will still exist in 10 years was given by 19 out of 90 respondents, which means that 21.1% of internal auditors consider that the existence of their job is not threatened in any way by 2033. This may be a lot or a little, but if we look at the opinion writers, we do not find anyone who questioned the existence of the internal auditor's job. In practice, the situation is different, with some internal auditors seeing their jobs under threat and 2% of respondents believing that it is certain that the internal auditor will no longer exist as a job for human beings in 10 years' time.

In order to explore the question of what threatens the job and, thus, the profession of internal auditor, two variables were designed to address this. The first measure was how many internal audit tasks respondents believed AI would take over in 10 years' time.

We asked respondents: **"How many internal audit tasks will be done by artificial intelligence in 10 years' time? Note: A Mark of 100 means the AI will perform 100% of the internal auditing tasks".**

Respondents' answers on how many internal audit tasks will be performed by AI in 10 years' time are fairly normally distributed. The normality of the distribution is shown in Figure 5.2 *(n* = 86).

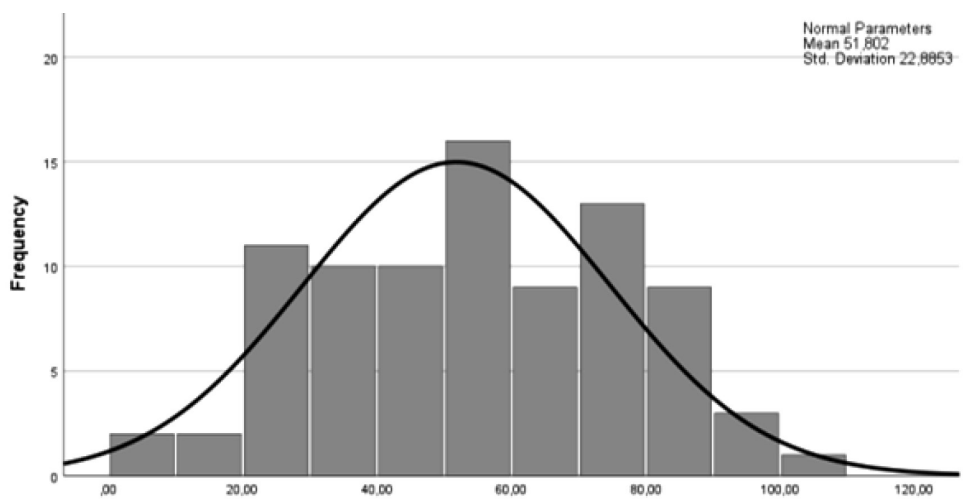

Figure 5.2. One-sample Kolmogorov-Smirnov normal test

Source: own study.

The results of the respondents' answers on how many internal audit tasks will be performed by AI in 10 years' time show that the average estimate of the internal auditors surveyed is 51.8%, with a standard deviation of 22.89 (*n* = 86), which can be

interpreted as meaning that, on average, the respondents believe that AI will perform less than 52% of the tasks of internal audit activities in 10 years' time. The results of the responses collected for the analysed question are also shown in Figure 5.3.

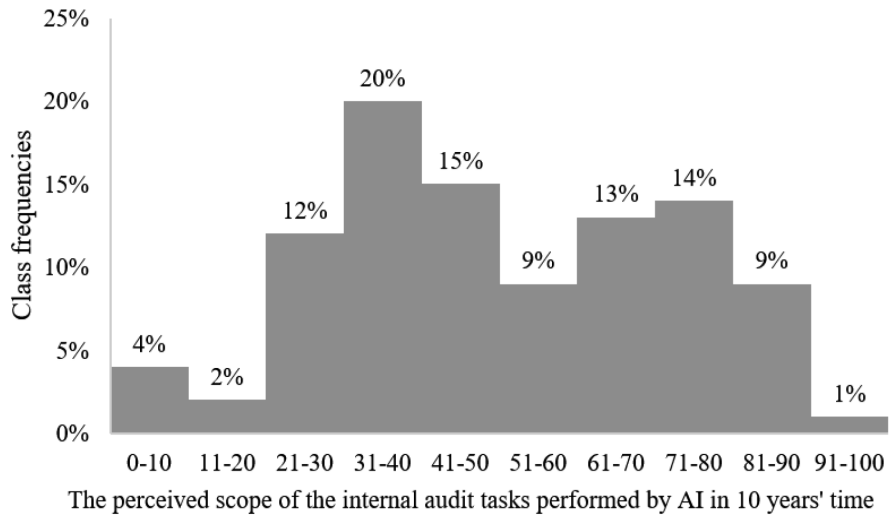

Figure 5.3. AI takeover of internal audit tasks in 10 years' time

Source: own study.

The results of the data collected show that only 1% of the internal auditors surveyed believe that AI will do absolutely zero of the internal audit tasks in the future, as well as 1% of the respondents believe that in 10 years' time, AI will do all the internal audit tasks by itself. The opinions of internal auditors on how many internal audit tasks AI will perform are mixed. The answers of respondents are very scattered, with 20% of respondents (the largest group) believing that AI will perform between 31% and 40% of internal audit tasks in 10 years' time, and the second largest group, with 14% of respondents, believing that AI will perform between 71% and 80% of internal audit tasks in 10 years' time. Based on these results, we believe that AI will largely determine the future of internal audit, and it is high time that internal audit pay more attention to this area. The third question in our survey was also dedicated to the future of internal audit. This question gathered a large number of descriptive responses with respondents' thoughts on the future of the internal audit profession.

As expected, the topics around AI were featured most frequently in the responses of internal auditors to our key open-ended question, which asked: **"What are your thoughts on the future existence and changes of internal audit over the next 10 years? Please briefly write down your thoughts!"**

Of the 91 internal auditors, 72 answered this question. The fact that the majority of respondents answered this question and the length of the answers received suggests

that internal auditors themselves feel that a critical moment has arrived for the future of internal auditing and the job of internal auditors.

In their replies, the internal auditors briefly described their vision of the workplace and internal audit in the 10-year future. The longest answer was a full page, and the shortest was two words. We have conducted a content analysis of the collected responses and present the results below. The most frequent responses were that in the future, their workplace will place a strong emphasis on the use and control of information technology and that they foresee changes in their work in the form of strong support for internal auditors from AI. In second place is a group of respondents who predict that everything will be the same in the field of internal audit as it is today and that the future of work will only see an increase in consultancy engagements, such as process improvement, finding strategic competitive advantages and helping to formulate strategies, were the most similar in terms of the range of related responses. From a several similar or typical responses, we have selected up to three typical (repeated) responses from respondents, which we believe provide a good illustration of how the internal auditors in the sample envisage the future of internal audit (responses are taken verbatim from the survey):

"I believe that the existence of an internal audit is absolutely necessary in the future, but there will be major changes in the way it operates. The process will be largely automated. Personal contact with auditees, knowledge of the organisation's work processes and interpretation of findings will still be important. The emphasis will be on IT, so additional skills will be required. There will be more consultancy work (e.g. improving processes, looking for competitive advantages)."

"Internal audit will have to adapt to the fast pace of change. The time it takes to perform and document the procedures carried out is sometimes not competitive with other areas of the organisation. With its analytical thinking skills, its access to all areas, and its comprehensive overview and knowledge of the organisation, it should remain an important and very useful link to the organisation. However, if auditors are too focused on assessing past practices, internal audit will lose its relevance."

"More AI work on routine tasks, more involvement of the internal auditor as a person in strategic discussions with management."

From the other responses collected, where the internal auditors in the sample are not thinking about their future or have not yet formed an idea of how their work will be in the future, we also carry over some typical responses. For example:

(1) "I have no idea what internal audit will be like in the future....";
(2) "I'm not thinking that far into the future...";
(3) "I'll be retired by then...";

or the short and succinct thought of one respondent:

(4) "Drastic changes!!!".

The content analysis method was used to examine the responses collected, and the key findings on the 10-year view of the future of internal auditors can be summarised in a few areas, namely:

1) The impact of AI on internal auditing in 10 years will be significant.

- AI will take on many routine and administrative tasks, such as checking data, looking for outliers and comparing against standards.
- AI will enable faster and more comprehensive analysis of large amounts of data.
- AI will help detect anomalies and potential risks.
- The human factor, or the internal auditor as a human, will still be needed to judge the results of AI, think critically, and accept the conclusions.

2) There are changes in the tasks of internal auditors.

- The focus will be on strategic advice and assisting management in achieving the organisation's objectives.
- The increased focus will be on IT audit and information security, especially in relation to the use of AI tools.
- There will be a need to develop new competencies for auditors, such as analytical thinking, knowledge of IT tools and the ability to interpret data.
- There will be an increased use of automated controls and continuous audit tools.
- There will be a need to work with external specialists on complex tasks.

3) Internal auditors will have to change and adapt to the new circumstances.

- The profession will remain important, but it will change dramatically.
- Auditors will need to be more flexible, innovative and able to learn new skills.
- The role of the internal auditor will become more advisory and focused on adding value to the organisation.
- The human factor will still be key to judgement, ethics and communication.
- AI will need to be used as a tool to enable auditors to work faster and better.
- Internal auditors will need to actively prepare for the future by developing new competencies and adopting new technologies. It will be important to work with management and other stakeholders to shape the future of internal audit. It will also be necessary to monitor the development of AI and other technologies and assess their impact on auditors' work.

Additional findings from the responses collected include:

- The role of internal audit will continue to evolve and adapt to new challenges.
- The human factor will continue to be key to the success of internal audit.

The biggest unknown and the greatest uncertainty is, therefore, AI. Many respondents say they do not trust AI today. This is and can be one of the key areas for internal auditors to focus on in developing their internal audit and professional competencies. Chambers (2024) writes differently about the impact of AI on internal auditing, having collected over 1,000 responses on its website in early 2024 to a question on what internal auditors think about the future of internal auditing. Chambers (2024) says that from the responses of internal auditors, it was found that two threats to the existence of the internal auditor did not rank in the top three

risks. These were "AI taking over part or all of our role", with only 17% of respondents rating it as their top three risks, and "inability to meet new IIA standards" with 5% of respondents (Chambers, 2024).

Let us look at a few specifically selected responses from respondents to our survey on AI and their work. Our results show that 96% of respondents believe AI will be a large part of internal audits in the next 10 years. We have analysed some of the responses collected from respondents on the topic of AI taking over internal audit tasks. Here are some interesting reflections:

"We could already do certain continuous auditing processes with the help of artificial intelligence."

"Artificial intelligence can help internal auditors with planning procedures, but not with the audit itself. This represents some 30% of the internal auditors' work (I estimate that the total planning procedures cover some 40% of the time of an audit). If there are reports of deviations already detected, the internal auditor will still have to examine them, assess the risk and the impact on the business and make recommendations for improvement. It is expected that this will enable the internal auditor to carry out the same audit more quickly. However, this should take into account the more frequent audits resulting from the audit of individual programmes – specifically on the audit of programme records in compliance with legislation and internal rules, controls to detect indications of deviations and errors and fraud..., so I also see no reason why the profession of internal auditing should die out. Moreover, artificial intelligence will not be free either, so it will be up to investors to decide whether to buy it to replace internal auditors. I estimate that in the future, there will be an increase in the number of audits of information systems, with a focus on auditing applications, which will require the auditor to have knowledge of programming, the processes supported by the application..., and a basis of economic and legal knowledge and other disciplines of the business, or programmers will also start to carry out audits and participate in audit teams."

"There is certainly 30% of data handling, pattern recognition, analytical processes, etc., which can be replaced by artificial intelligence."

"AI will make it possible to carry out much more sophisticated and complex analyses in less time. But it will still be the internal auditor who will manage the AI and draw the final judgements and conclusions".

On average, therefore, respondents believe that AI will replace a good half of the internal audit work (see results of the second variable and Figure 5.3 of this chapter) but that it will not be able to replace all that internal audit represents and that the presence of the human factor will still be needed in terms of control and the interpretation of findings. Respondents believe that this is due to advances in technology and digitisation and that AI will help in the execution of planned procedures and save time for internal auditors to collect and process data, leaving them more time to assess and interpret the results obtained critically and to discuss them with the clients of the business.

Among the answers on the future of internal audit, it is also worth highlighting the answers on professional competence. Respondents consider that the required qualification has a major impact on internal auditors. Therefore, continuous training will continue to be a constant feature of internal audit. According to the respondents, complexity and dynamism in operations are also very important. Therefore, the internal auditor's business and work will become more dynamic and complex in the future, which will also be reflected in the qualifications required.

We also carried out tests for independent samples by gender, work experience, age, different activities, and according to the legally mandatory presence of internal audit in organisations, and the t-tests of the means of all possible groups were not statistically significantly different for both the variable future existence of internal audit and the variable extent of internal audit tasks taken on by AIs.

Finally, we tested whether there is a correlation between the opinion on the existence of an internal auditor post in 10 years' time and the percentage of internal audit engagements expected to be undertaken by AI in 10 years' time (Figure 5.4).

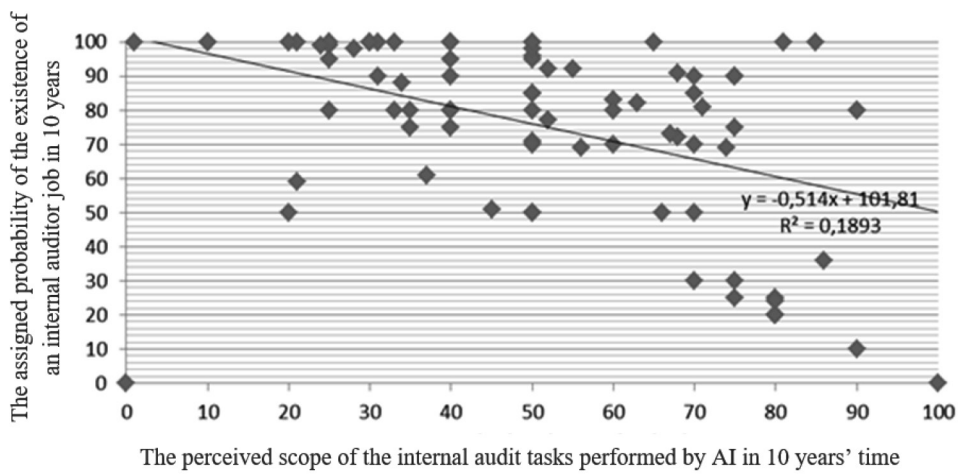

Figure 5.4. Scatter plot illustrating the relationship between the two study variables

Source: own study.

Figure 5.4 shows a correlation between two analysed variables with a coefficient of determination (R^2) of 0.1893. This means that 18.93% of the variation in the probability of the existence of an internal auditor post can be explained by the extent to which AI takes on internal audit work. Also, the Pearson Correlation calculation showed a statistically significant correlation (Sig. (2-tailed) <0.001) and the Pearson Correlation value of -0.427. This means that there is a medium-strong negative correlation between the existence of an internal auditor job and the extent of AI taking

on internal audit tasks, or in other words, the respondents' opinion indicates that the more internal audit tasks are taken on by AI, the lower the respondents' assessment that an internal auditor job will exist. Despite this finding, we believe that the future of the job and the profession of internal auditors is not as bleak as this correlation makes it seem. In the next section, we will consider what we see as the future and changes in internal auditing.

5.4. Conclusions

Internal audit is an activity that can significantly contribute to improving the efficiency and effectiveness of all organisations. In order to achieve this, it is necessary to continuously review the performance and effectiveness of all it represents. Internal auditors help an organisation achieve its objectives by assessing and providing advice. They need to keep abreast of all technological, business and societal changes occurring today and in the future so that they can add value to the organisation as much as possible.

With the Fourth Industrial Revolution, we are all caught up in the tide of change. 3D printing, AI, the sharing economy, the Internet of Things, self-driving cars and other changes are just "drops in the ocean" of innovations that will soon become commonplace. Of these, it is safe to say that AI will largely shape the future of internal auditing.

The tipping point for internal audit, expected to be reached by 2025-2030, suggests that 30% of internal audit tasks will then be able to be performed by AI. Deloitte (n.d.) forecasts the uptake of robotic process automation (RPA) in internal audit. The authors (Deloitte, n.d) argue that RPA can bring a number of benefits, such as increased efficiency, reduced costs and improved audit quality. RPA is expected to make audit processes more dynamic, safe, and reliable, and, in short, they are of higher quality (Mookerjee and Rao, 2021).

The most important technologies that enable intelligence, flexibility and interconnectivity include technological sensors, cyber-physical systems, the Internet of Services and the Internet of Things. Future sensors will have the function of data acquisition and processing, will be able to communicate, and will thus completely replace humans in data collection (Abdelli et al., 2021; Chen et al., 2019).

In the future, internal audit work will be facilitated by a number of software solutions, thanks to advanced technology and the associated digitisation, as more and more software providers have been working in recent years to create these so--called audit and accounting solutions.

Technological innovation, the rapid development of AI, and political and macroeconomic pressures will all influence changes in all professions in the future, and internal auditing will be no different. In the future, internal auditing will be ubiquitous, simultaneous, continuous and uninterrupted, so plans will no longer be needed;

thus, this time will be dedicated to in-depth interviews and specific assignments for clients (SAP AG, 2019). Internal audit will offer the opportunity to transform in the coming years and become indispensable for effective governance, control, and risk management. An innate sense of risk perception, technological dexterity and technological fearlessness, constant curiosity and professional scepticism, intellectual honesty, foresight of ethical changes or problems, and inheritance of professions that are not necessary are the qualities that internal auditors will need to have developed in 10 years. They will be essential for the effective performance of internal auditing work.

However, we should not forget that AI also brings new risks, and this is the field of new services for internal auditing. Potential risks with the use of AI nowadays manifest themselves as the problem of accidents in machine learning systems, defined as unintentional and harmful behaviour that can occur due to poor design of AI systems in the real world (Amodei et al., 2016).

Computing technologies by 2033 are predicted to be completely transformed (Fox, 2024), e.g. two such architectures are in advanced stages of development. The first, quantum computing, and the second, neuromorphic chips, mimic the design of the human brain.

Of particular interest for internal auditing by 2030 will be the field of quantum computers (Fox, 2024). Quantum computers will be so powerful – and with such long coherence times – that they can unlock a previous high-level encryption of hundreds of digits in a matter of seconds. They will emerge as a revolutionary alternative to "classical" computers. While the latter is limited to binary ones and zeros, quantum systems have the advantage of using multiple values simultaneously, allowing them to work with astronomically large amounts of data and numbers that would normally take millions or billions of years to calculate. The arrival of quantum computers in 2030 will bring new data security risks. Quantum computers (Fox, 2024) may provide vast amounts of users' personal data and the ability to hack into RSA-2048 keys, which also risks revealing state and industrial secrets and information relating to long-standing conspiracy theories, historical archives, etc. Quantum computers may also be able to provide information about the security of users' personal data. The website – https://www.futuretimeline.net/21stcentury/2031.htm – predicts that the media reports of this time (2030) will be full of news about intrusions into the information systems of organisations and individuals and about leaks of information, encouraging greater scrutiny of quantum computing technology and encryption in general.

The development of AI, therefore, also brings many opportunities for fraud and abuse. It will be possible to design immoral AI to attack specific targets, steal, kill and more in the name of engineering. There is already a TV series about this (Mr. Robot, https://en.wikipedia.org/wiki/Mr._Robot); it will be possible to use mind-reading devices, access sensitive or confidential information of a targeted victim or implant false memories of the said victim (similar to the movie Inception, https://en.wikipedia.org/wiki/Inception). Whether the AI can violate rights or carry out a killing and will

be recognised as a legal person is still unknown. Anyone interested in learning more about these predictions should read https://www.quantumrun.com/.

The key question of research is whether AI will take over the key oversight tasks in 10 years' time. Thus, will the internal auditor no longer be needed? In this case, the post of internal auditor would indeed be at risk. Is it only a matter of time before all aspects of world affairs are controlled by a super-intelligent entity made up of billions of inorganic minds acting in concert? No one is predicting this by 2033, so we believe the internal auditor in 10 years' time will still be its own entity and will be a human and not an AI.

What does all this mean for the future of internal audit itself? From the results of the survey and the thoughts of the writers on the future of internal audit, it can be summarised that today, only a small percentage of internal auditors (respondents) agree that there will not be major changes in internal audit in the future. Drastic changes will and are needed, not only because of AI but also because the use of AI should be integrated into internal auditing immediately. Therefore, the first suggestion of this chapter is that we need to increase the proportion of internal auditors who believe that there will be major changes in internal auditing in the future and that AI is important for internal auditing both as a tool and as a risk that needs more attention from internal auditors. We all need to join in this thinking, including those who believe that change is not expected or currently perceptible or that it is too far away for them to think about today. Those who will be retired at that time will still have a significant dependence on society and how it works because pensions, healthcare, culture, etc., will not exist without our descendants and the environment (the state).

It is inevitable that we think about internal audit in 2033 today. Thinking about the future is not easy. There are many versions of the future and many unknowns, but without trying to know them, we know we are on the wrong track. AI is not a bad thing. AI will make internal audit different, better and hopefully more accepted by stakeholders. AI has and will shape the future of internal audit. The report of AuditBoard highlights huge opportunities for internal audit in two main directions: integrating AI into internal audit processes and providing guidance and assurance to organisations (AuditBoard, 2023). AI tools such as ChatGPT are presented as capability multipliers that can improve planning and decision-making. The report encourages internal auditors to educate themselves on the potential of AI, as top talent expects organisations to take advantage of next-generation AI technologies.

Chambers (2024) believes that internal auditors need to change if they are to survive. Changes in internal auditing can be predicted through 7 strategic risks that internal auditors need to be alert to in the future. These are (Chambers, 2024):

1) **failure to attract and retain talent** – this risk ranked first among US internal auditors. It is not surprising, given the general shortage of talent in overheated economies around the world. However, this risk also reflects the challenges (as many other strategic risks show) of recruiting and retaining skills that are critical to the mission of the profession – especially technology.

2) **inability to make effective use of technology** – as with the talent risk, the ability to leverage technology in the delivery of the internal audit mission remained second place in each of the surveys. Leveraging technology solutions is no longer considered a leading practice in the profession. Instead, it has become essential for delivering value and meeting stakeholder expectations. Nevertheless, the importance of this risk reflects the realisation that we still have much work to do to harness the power of technology, as internal audit is still under-active.
3) **failure to use AI as a multiplier of capacity** – in the past year, we have witnessed a stunning acceleration in the adoption/expansion of AI. It is, therefore, not surprising that the profession's ability to harness AI is now seen as a strategic imperative. Generative AI presents enormous opportunities for the profession, but today, "no more than 10% of internal auditors use generative AI in any way in their work, and 50-75% do not. Every internal auditor should strive to explore or implement at least generative AI in internal audit". This is a strategic risk that will not go away.
4) **lack of IT expertise** – this strategic risk is different from No 2. Here, internal auditors acknowledge that we lack skills and expertise in auditing technology risks. The gap is likely to widen as the risks of AI in our organisations become more pronounced.
5) **failure to identify critical risks** – not surprisingly, this continues to be seen as a strategic risk. Fortunately, it is no longer to be seen in the top three. However, for those internal audit departments that fail to assess and address the critical risks facing their organisation, this risk can be existential,
6) **stakeholder audit/oversight fatigue** – the first quarter of the 21st century is almost in the history books. One of the key trends in the corporate sector has been the proliferation of second and third lines of defence and risk management functions such as compliance and even internal audit itself. Some industries, such as financial services, have seen exponential growth in these functions. For internal audit, the risk is the inability to differentiate the value we provide from that of second-line functions. Stakeholder fatigue refers to the risk that our stakeholders will not support us (especially in times of economic crisis) because they believe there are "too many supervisors and not enough practitioners".
7) **failure to identify emerging risks** – the profession remains concerned that challenges in identifying emerging risks will lead to inevitable "where has the internal auditor been" moments. It is striking that this risk has diminished at a time when risk chaos and uncertainty have never been greater.

In conclusion, in the future, internal audit needs to be better able to present itself to stakeholders and thus also act as a key player in helping organisations to identify and understand the use of AI risks, advise on processes and governance, monitor regulatory progress and provide assurance on compliance readiness. Internal audit should not hesitate to invest in AI as it represents a tremendous opportunity for the profession, without which its very existence may be threatened.

Do not turn a blind eye; be bold. AI and all future technologies and changes will have both good and bad implications for internal audit, and we need to understand both if we are to help manage risk and add knowledge and value to our profession and our organisation. Be brave and start with the future today, and let us hope AI does not turn our blue screen on.

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Chapter 6

Enhancing Integrated Reporting Processes through the Integration of Artificial Intelligence into Management Systems

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Whether we like it or not, we are witnessing how the Earth, as we knew it, remains in the past. In the last century, technologies have evolved so much that people are becoming preoccupied with their discoveries. Sometimes, inventions

are so comprehensive that they overwhelm individuals entirely, prompting them to rush to investigate the consequences or implications of the innovation. On the other hand, researchers are attempting to propose solutions and practices to promote environmentally conscious behaviour, urging companies not only to report on financial aspects but also to reveal the responsible actions they are implementing. In this context, we intend to assess how one of the most popular inventions in the field of artificial intelligence (AI), Chat-GPT, can influence integrated reporting processes through its implementation in the management system.

The aim of this study is to analyse and highlight how AI can support and optimise integrated reporting processes, providing a detailed perspective on its potential to transform how organisations manage and communicate their financial and non-financial performance. As part of this research endeavour, we have established a series of objectives to be achieved, such as identifying scientific papers that address reporting and AI, the bibliometric analysis of the identified research, applying research methods to investigate the studies, and the systematisation of findings and formulation of conclusions. In this context, we employed various research methods, including bibliometric analysis, comparison of previous studies, and the induction and deduction of significant ideas based on the findings of researchers in the field.

This chapter consists of four parts. Section 6.1 presents the results of the bibliometric analysis on the links between AI and non-financial reporting. Section 6.2 elaborates on the opportunities and challenges of AI in integrated reporting. Section 6.3 discusses the main issues related to AI implementation. The last section concludes the chapter, presents the advantages and disadvantages of AI implementation in integrated reporting, and delineates the future research directions.

6.1. Results of the Bibliometric Analysis on the Links between Artificial Intelligence and Non-Financial Reporting

The impact of corporate social responsibility and integrated reporting in promoting sustainable development is undeniable. Integrated reporting, which combines financial and non-financial information, provides a holistic view of a company's performance and its impact on sustainability (Putri et al., 2023). It enhances corporate accountability through transparent practices, stakeholder engagement, and the emphasis on long--term value creation, aiding in risk management and potentially providing a competitive advantage to companies (Nazir, 2023). Integrated reporting is increasingly gaining popularity among researchers and practitioners, receiving both acclaim and criticism. Therefore, to meet the information needs of investors and other capital providers, there is a constant need for adaptation (Efimova and Rozhnova, 2019). In this regard, researchers agree on the necessity to expand studies on how AI technologies can be applied in reporting, particularly as the field evolves with new capabilities, such as machine learning and natural language processing (Sutton et al., 2016).

To identify publications relevant to our research theme, we conducted a query in the Web of Science database, setting the following search parameters: all fields must contain the words: "integrated reporting", or "integrated reports", or "sustainability reporting", or "sustainability reports", or "ESG reports", or "ESG reporting" and "artificial intelligence". We did not set a time frame for publication years, as this topic has gained popularity in recent decades. Consequently, we obtained a sample of 34 scientific articles that met the criteria. This outcome indicates a relatively low volume of research addressing the implications of implementing AI in the integrated reporting process, thereby highlighting the need for in-depth and systematic exploration. Although the topic has been identified and addressed in academic research, there remains substantial scope for expanding and deepening knowledge in this area. Therefore, this research not only contributes to enhancing the specialised literature but also emphasises the importance of future studies that could aid in a better understanding of the impacts of AI on corporate reporting.

Although the current level of knowledge on the implications of AI in corporate reporting processes is limited, the mentioned 34 studies explored the thematic intersection between various types of reports presenting non-financial information and the development of AI in this area.

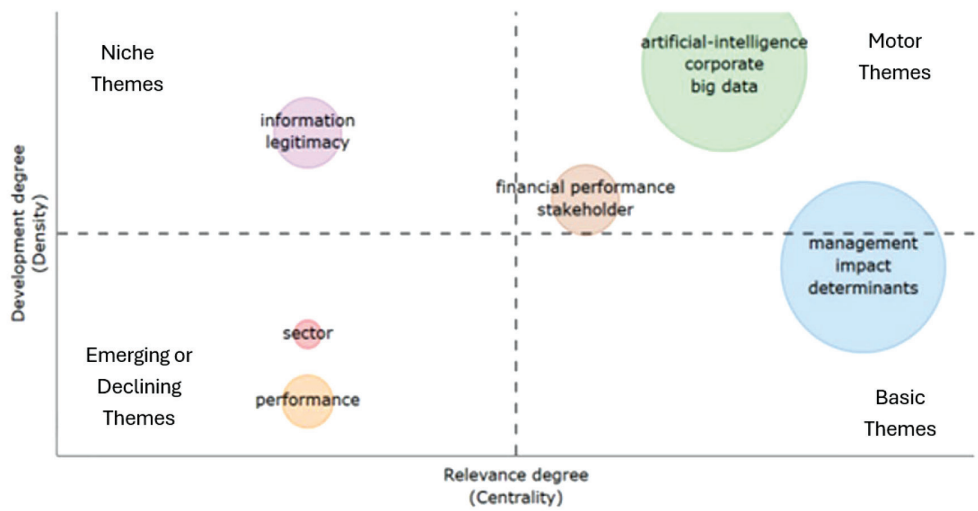

Figure 6.1. Thematic map related to AI and integrated reporting scientific papers

Source: created by the author in Biblioshiny based on the Web of Science database.

The most important quadrant of the map illustrated above is the motor themes that indicate the direction in which research on the correlation between integrated reporting and AI is developing. Two important clusters containing keywords such as: "financial performance", "stakeholder", "corporate", and "big data" can be observed.

These are also considered themes that drive research and have a large influence on other research themes.

The basic themes associated with the database uploaded to Biblioshiny are "management", "impact", and "determinants". Although they are important themes, they are not as developed as the motor themes but have a high enough centrality, indicating that they are fundamental to research in the field of non-financial reporting and AI.

The quadrant of emerging or declining themes contains two clusters: "sector" and "performance". The centrality score of these clusters is 0, indicating that they are not central themes but have a density that may suggest they are still topical.

Niche themes include a single cluster composed of the words "information" and "legitimacy". Considering its lower density and zero centrality, it can be interpreted as a particular topic that has not yet received much attention in the specialised literature.

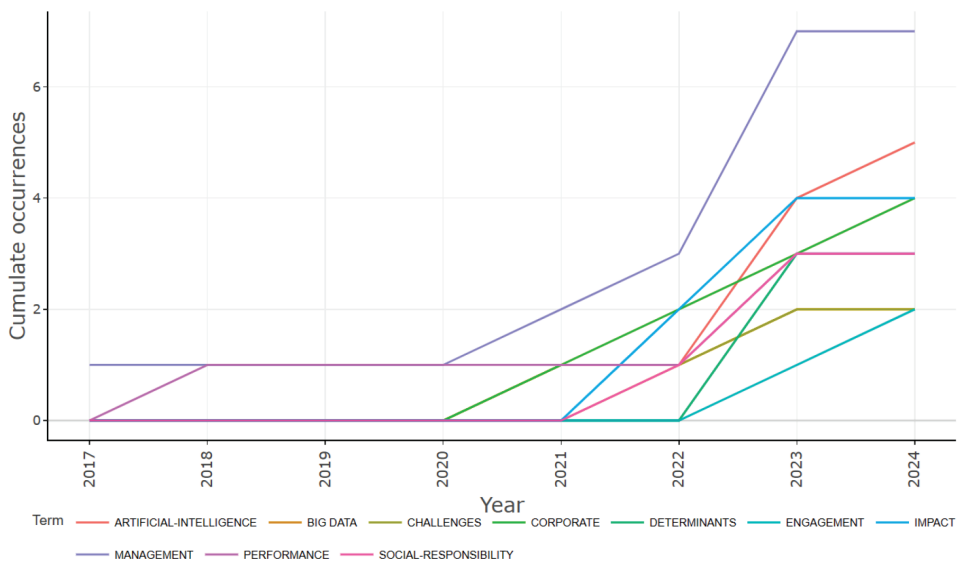

Figure 6.2. Word frequency over time, related to AI and integrated reporting scientific papers

Source: created by the author in Biblioshiny based on the Web of Science database.

The above chart displays the cumulative trends of the keywords plus frequency over time, from 2017 to 2024, presenting data on how interest in different research topics fluctuates over the years.

It can be observed that there is a growing trend in the research community's focus on terms such as "management", "artificial intelligence" and "corporate" indicating that these topics are of current interest and also relevant for future studies. The terms "impact", "determinants", "performance" and "social responsibility" have been

addressed more recently but show considerable growth, indicating a shift in the research agendas of scientists.

In the study conducted by Lombardi and Secundo (2021), the research directions for the digital transformation of corporate reporting were delineated, which resonated with the results obtained from the analysis in Biblioshiny.

Figure 6.3. Key research directions regarding the digital transformation of corporate reporting

Source: (Lombardi and Secundo, 2021).

The directions highlighted above emphasise the increasingly pronounced interaction between digital technologies and corporate reporting processes, underscoring the need for further research to understand and leverage the potential of digital technologies to enhance transparency, engagement, and decision-making in corporate reporting. Studies indicate that adopting digital technologies enhances the usefulness of reports, making them interactive, user-friendly, and detailed, which ensures a better understanding and provides another reason for their application (Efimova and Rozhnova, 2019). A similar perspective is found in another work, suggesting that the application of digital technologies can improve sustainability reporting, which, in turn, can support economic growth and environmental protection (Mehedintu and Soava, 2023).

AI is seen as a transformative force in accounting, offering more intelligent systems compared to traditional information systems, with large companies heavily investing in AI technologies for this purpose (Damerji and Salimi, 2021). In a study conducted by Lee and Tajudeen (2020), the impact of using AI-based accounting software among companies in Malaysia was analysed with the aim of understanding its benefits and how it is implemented in accounting functions. The experience of the analysed companies confirmed the authors' reasoning that the adoption of AI improves efficiency and productivity, enhances process governance, and reduces personnel expenses (Lee and Tajudeen, 2020).

Other researchers have examined the impact of AI on ESG management. It was identified that AI application streamlines the data analysis and decision-

-making process. Simultaneously, it enables real-time process monitoring and scalability, processing large volumes of data to provide accurate assessments of ESG performance (Cucari et al., 2023).

Surprisingly, to date, no study has addressed the adoption of AI in integrated reporting processes, which is a key driver for the desire to contribute current information on this topic. One of the few research efforts that correlate AI with integrated reporting highlights the absence of a standardised framework for reporting AI and CE activities in IR practices to ensure effective communication of social responsibility efforts to stakeholders (Doni et al., 2023).

Thus, the necessity for ongoing research on how AI can evolve and enhance corporate reporting is highlighted. As technologies advance and develop, it will be critical to test and examine trends to understand the impact and potential of AI in optimising integrated reporting processes and beyond.

6.2. Opportunities and Challenges of Artificial Intelligence in Integrated Reporting

It is forecasted that by the year 2030, the market for ESG-relevant software will experience significant growth, driven by the implementation of responsible actions by enterprises, as well as an increased awareness of sustainability among the population (Cucari et al., 2023). This estimate is confirmed with each passing day, alongside the evolution of AI-based technologies that are spreading across all sectors.

Successful integration of AI with management and reporting systems requires not only technical compatibility but also a strategic approach to ensure that AI enhances rather than disrupts existing processes (De Villiers et al., 2024). This raises the pertinent question of how this integration will be made possible and what steps must be taken to create an effective implementation framework.

In the study published by Farooq and Nadeem, the non-financial reporting process was outlined in seven stages, where technologies can be applied: defining the scope and objectives, materiality assessment, data collection and analysis, compiling the report, external assurance, dissemination, and performance improvement (Farooq and Nadeem, 2023). By addressing the stages of the non-financial reporting process, it becomes clear that the integration of advanced technologies can bring about significant changes in how companies manage and communicate their corporate responsibility. This progression naturally leads to a related and equally core topic: the integration of AI into corporate governance structures.

The scenarios mentioned provide a framework for understanding potential trajectories of AI integration in corporate governance, highlighting the progression from AI as a tool for enhancing human decision-making processes to AI as an autonomous entity capable of self-evolution and governance. This evolution addresses important questions regarding responsibility, control, and the future role of human directors in corporate governance structures.

Figure 6.4. AI integration scenarios in corporate governance structures

Source: (Hilb, 2020).

To directly consult AI about the implications of AI in integrated reporting, we formulated the research question, "How can artificial intelligence integration enhance integrated reporting processes within management systems?" This inquiry was addressed to the latest version of the tool created by OpenAI, ChatGPT 4.0. Through this query, we aimed to obtain a broader response, the points of which we would confirm or refute by referencing studies published by various researchers in the field.

Answer received from Chat GPT 4.0:

"Artificial intelligence (AI) can significantly enhance integrated reporting processes within management systems by introducing efficiency, accuracy, and deeper insights. Integrated reporting aims to provide a holistic view of an organisation's performance, encompassing financial, environmental, social, and governance information. Here's how AI can play a pivotal role in improving these processes:

1) **Data Aggregation and Processing:** AI can automate the collection and processing of vast amounts of data from various internal and external sources. This automation reduces the time and effort required for data collection, ensuring that the integrated reports are based on the most current and comprehensive data available.
2) **Enhanced Analytical Capabilities:** AI algorithms can analyse complex and large datasets more efficiently than traditional methods. They can identify patterns, trends, and correlations that might not be evident through manual analysis. This capability can provide deeper insights into the financial, social, and environmental performance of an organisation, enriching the integrated reporting process.
3) **Predictive Analytics:** AI can employ predictive analytics to forecast future trends based on historical and current data. These forecasts can inform stakeholders about potential future scenarios, helping them make more informed decisions. Predictive insights can be a valuable addition to integrated reports, offering a forward-looking perspective alongside historical data.
4) **Risk Management:** AI can enhance the risk management aspect of integrated reporting by identifying and assessing potential risks more effectively. By analysing data patterns, AI can predict potential risks and their impacts, allowing organisations to address these risks proactively in their reports and decision-making processes.
5) **Stakeholder Engagement:** AI-driven data analysis can provide insights tailored to the interests and concerns of various stakeholders, enhancing the relevance and usefulness of integrated reports. By understanding stakeholder preferences

and concerns through data analysis, organisations can present information in a more targeted and engaging manner.

6) **Customisation and Personalisation:** AI can tailor reports to the specific needs and preferences of different stakeholders. By analysing user interaction data, AI can help organisations present the most relevant information to each stakeholder group, enhancing the user experience and effectiveness of the reports.
7) **Real-time Reporting:** AI enables real-time data analysis and reporting, allowing organisations to provide up-to-date information to stakeholders. This real-time capability can be particularly valuable in rapidly changing environments, ensuring that integrated reports reflect the most current state of the organisation.
8) **Consistency and Reliability:** AI can help ensure the consistency and reliability of data across different sections of an integrated report. By automating data validation and consistency checks, AI can reduce errors and discrepancies, enhancing the credibility of the reports.
9) **Sustainability Insights:** In the context of environmental and social governance (ESG), AI can provide valuable insights into sustainability practices and their impacts. AI-driven analysis can help organisations understand and communicate their sustainability performance, aligning with the increasing emphasis on ESG in integrated reporting.
10) **Continuous Improvement:** AI systems can learn from feedback and data over time, leading to continuous improvement in the reporting process. This iterative learning process can refine the accuracy, relevance, and effectiveness of integrated reports, ensuring they evolve in line with stakeholder expectations and organisational goals."

Points 1-4 indicated by ChatGPT 4.0 emphasise the role of data collection, processing and analysis in improving the integrated reporting processes. Indeed, researchers corroborate the assertions formulated by ChatGPT 4.0. AI is perceived as a tool capable of analysing large amounts of data to enhance the accuracy and reliability of sustainability reports (Yonis Mousa, 2023). However, for AI to provide meaningful insights and improve the reporting process, the uploaded databases must be precise, comprehensive, and consistently managed (De Villiers et al., 2024). In their studies, some researchers have also applied systematic textual analysis using AI to explore integrated reports from listed European companies, thus creating a synthetic measure of sustainability disclosure (Camodeca et al., 2018).

AI systems can process large volumes of data much faster than human analysts, enhancing the efficiency of report preparation and review (Yonis Mousa, 2023). Additionally, AI can conduct complex analyses to support non-financial reporting, providing a more comprehensive picture of an organisation's sustainability and social impact (De Villiers et al.; Putri et al., 2023). At the same time, the data processing speed is significantly higher than manual processing (Lombardi and Secundo, 2021).

The predictive capabilities of AI can also be essential in identifying and managing potential risks and trends in sustainability performance (Farooq and Nadeem, 2023). They provide a deeper understanding, helping managers make timely-informed decisions (Yonis Mousa, 2023; Lombardi and Secundo, 2020). AI's ability to predict outcomes also aids in strategic planning and risk management, providing insights that may not be apparent to human decision-makers (Hilb, 2020).

Although the use of AI offers significant benefits in information processing and decision-making, there are also some risks, especially when the AI system encounters unexpected situations or when logical errors occur in AI algorithms (Yonis Mousa, 2023). Additionally, the efficiency and accuracy of data analysis may vary if they are uploaded in a language that has not been sufficiently tested in the AI tool (Hillebrand et al., 2023).

ChatGPT 4.0 also stressed the role of AI-driven tools in engaging stakeholders and addressing their needs (points 5-6). Understanding how stakeholders perceive reports generated by AI is essential, as stakeholder trust can have a significant impact on its acceptance and effectiveness (De Villiers et al., 2024). Digital technologies can transform the corporate reporting process, making it more efficient and resulting in greater transparency for stakeholders, thereby increasing stakeholder trust (Lombardi and Secundo, 2021; Yonis Mousa, 2023).

Digital reports can be personalised according to the users' needs, offering interactive features that allow stakeholders to delve deeper into the data (Efimova and Rozhnova, 2019). This function is important from the perspective of companies adapting to stakeholders' requirements, thus helping to establish more efficient communication with them.

However, companies' stakeholders may have different perspectives on reports generated by AI (De Villiers et al., 2024). Some may be sceptical of the accuracy and reliability of data analysed and systematised without human involvement, with the risk of unforeseen behaviours of AI algorithms when faced with new situations that were not indicated in the initial instructions (Yonis Mousa, 2023).

Points 7-10 indicated by ChatGPT 4.0 address the issues of timeliness, consistency, sustainability insights and continuous improvement. One advantage of adopting AI is the real-time analysis and monitoring of financial data, facilitating quick decision-making and fraud detection (Han et al., 2023). Moreover, due to the timeliness of the data, more informed decisions can be made (Hilb, 2020). Furthermore, AI offers the ability to monitor ESG trends and risks in companies in real-time (Cucari et al., 2023).

AI can significantly improve the quality of sustainability reports by providing more precise, reliable, and comprehensive data analysis (Yonis Mousa, 2023). The reliability of reports is a significant concern for reporting entities. AI algorithms can assist reporters in this regard by assessing data with greater accuracy, thereby enhancing reliability (Han et al., 2023).

6.3. Challenges of Artificial Intelligence Implementation

Among the major challenges of adopting AI is the establishment of ethical algorithms, underscoring the need for fairness, transparency, and accountability in implementing AI in management systems throughout integrated reporting processes (Nazir, 2023). The ethical implications of AI represent a significant concern, particularly concerning data confidentiality, potential bias in AI algorithms, and the accountability of AI-generated reports. These issues require clear guidance, standards, and regulatory frameworks to ensure the ethical use of AI (De Villiers et al., 2024; Nazir, 2023).

The implementation of AI can be complex and costly, requiring significant investments in equipment and training (Lee and Tajudeen, 2020; Lombardi and Secundo, 2021). Developing and maintaining an advanced AI system requires resources that many companies may be unable to afford (Hillebrand et al., 2023).

Another concern is that as AI becomes integrated into reporting processes, there will be an increasing need for qualified professionals in both AI and integrated reporting. This necessitates investments in training and development to equip professionals with the necessary skills (De Villiers et al., 2024; Nazir, 2023). Thus, there is a need to adapt accounting education to provide future professionals with the knowledge and skills required to work effectively with AI technologies (Sutton et al., 2016). According to Damerji and Salimi's study, the technological preparedness of accounting students and their perceptions of the ease of use and usefulness of AI technologies are significant predictors of their intention to adopt AI in their future careers (Damerji and Salimi, 2021). However, even training professionals with AI knowledge will not eliminate the risk of job reduction if tasks have been automated by AI and do not require human involvement (Lee and Tajudeen, 2020). This risk predominantly affects unskilled personnel who are responsible for manual data entry (Niehoff, 2022).

6.4. Conclusions

The integration of AI into management processes for integrated reporting represents a promising direction that offers vast opportunities for improving efficiency and accuracy in corporate reporting. Like any new field, it comes with both advantages and disadvantages that should not be overlooked and must be carefully weighed before making the decision to implement it.

Through our research, we have identified a series of advantages of implementing AI in integrated reporting, which include the ability to process and analyse large volumes of data rapidly and efficiently, improving the accuracy and reliability of data, as well as streamlining processes through automation. Additionally, AI can highlight future trends and risks, thus providing a solid foundation for informed and proactive decision--making. Moreover, the adoption of AI can contribute to increased transparency and

corporate accountability, which are essential aspects in the context of rising stakeholder expectations and sustainability standards.

However, some disadvantages have also been identified, such as ethical and confidentiality challenges, the complexity and costs of implementation, and the need for an adequate understanding of the technology by both professionals and stakeholders. The existence of a bias risk in algorithms and the potential implications of AI errors require strong ethical standards and regulatory frameworks. Moreover, the widespread adoption of AI in integrated reporting may lead to changes in the workforce dynamics, with the potential to reduce jobs involving repetitive and manual tasks.

Although the challenges are significant, the potential benefits of integrating AI into integrated reporting processes are substantial. These can transform how companies manage and communicate their performance, contributing to greater corporate responsibility and transparency. However, the success of implementation depends on a strategic approach, developing necessary skills among professionals, and establishing appropriate ethical and regulatory frameworks so that enterprises can understand the limits of AI usage.

Future research directions may include evaluating the impact of AI on the quality and relevance of information presented in integrated reports, studying the interaction between AI and human decision-making processes in the context of corporate governance and integrated reporting, analysing the ethical challenges and privacy issues associated with the use of AI in data collection and processing, exploring the impact of AI adoption on accounting and reporting professionals, and investigating the acceptance and perception of stakeholders towards reports generated with the help of AI, to better understand the impact on trust and investment decisions.

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Chapter 7

Artificial Intelligence in Accounting Business and Education: Theoretical Approach

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In an ever-changing world, the rapid development of technology and the recent boost of various artificial intelligence (AI) tools have impacted various fields, including business and accountancy education. The use, understanding and integration of AI reveal the theoretical issues and practical challenges. Understanding the impact of AI on these areas is critical for developing future business and educational strategies. AI is revolutionising traditional practices, improving data management and financial decision-making accuracy and efficiency. AI is not only transforming business processes; it is also driving change in learning and teaching methodologies. This shift requires a comprehensive theoretical investigation.

The purpose of the research is to explore the theoretical implications of AI in accounting business and education. Research objectives include:

- searching the largest database *Web of Science* (Clarivate Analytics) (*WoS*) for articles with the keywords AI and accounting, and analysing the data using *WoS* tools;

- analysing the keywords of selected articles using the *VOSviewer* tool;
- making a detailed analysis of the first 10 articles in the search list;
- screening the articles with the *RAYYAN* tool and conducting the systematic analysis using the main criteria of the articles.

The research methods include the process of literature analysis, which includes phases of searching for articles, analysis using *WoS*, *VOSviewer, and RAYYAN* tools, as well as manual detailed analysis of selected articles and systematic analysis according to the main criteria.

The chapter's content is divided into the following parts: Section 7.1 presents the design of the literature review process. Section 7.2 gives insight into the research and discusses various aspects of AI in accounting. Section 7.3. focuses on presenting the content of the papers selected under systematic analysis, which links the topic of AI in accounting with business and education aspects. The last section concludes the study and indicates directions for future research.

7.1. Design of Literature Review Process

The largest database, *Web of Science* (Clarivate Analytics) (*WoS*), was chosen to search for recent research. The *Web of Science* portfolio of research platforms and workflow tools helps researchers efficiently conduct disruptive research and advance their field, identify which research problems remain unsolved and the best opportunities to contribute, collaborate efficiently with the right peers, and share findings by publishing in the world's leading journals (Clarivate, 2024). In response to the chapter's topic, the search started with the main keywords: artificial intelligence (AI) and accounting (see Figure 7.1).

The search yielded 6,600 papers in a research period covering the last five years. The next step in the research analysis was to examine the categories and set the categories in response to the chapter topic. Figure 7.2 shows the distribution of research in the first 10 *WoS* categories.

The following *WoS* categories were used to capture the essence of the chapter topic: Computer Science Artificial Intelligence, Multidisciplinary, Business Finance, Economics, Business, Management, Education Educational Research, Social Sciences Interdisciplinary. Only articles were selected for further analysis. Complete records of articles were downloaded in RIS format for analysis by the *VOSviewer* tool. *VOSviewer* revealed five clusters with the strongest keywords: artificial intelligence, machine learning, big data, model, and management (Figure7.3).

Using the *VOSviewier* tool, the map of keyword occurrences was created with 7 as the minimum number of occurrences of a keyword, which resulted in 6 clusters with 119 items out of 5,144. Before the last step of preparation of the map, the list of keywords was revised, and duplicate keywords were removed. The total link strength was 2,182, and the total number of links was 1,361.

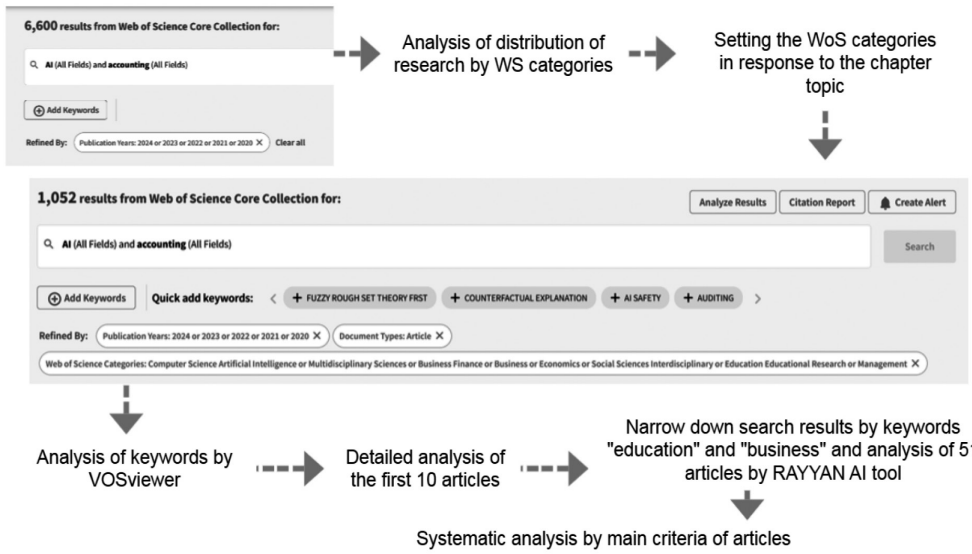

Figure 7.1. Literature analysis process

Source: own presentation.

Field: Web of Science Categories	Record Count	% of 6,600
Computer Science Artificial Intelligence	1,082	16.394%
Engineering Electrical Electronic	699	10.591%
Computer Science Information Systems	544	8.242%
Computer Science Interdisciplinary Applications	444	6.727%
Computer Science Theory Methods	394	5.970%
Environmental Sciences	301	4.561%
Telecommunications	282	4.273%
Robotics	223	3.379%
Materials Science Multidisciplinary	215	3.258%
Multidisciplinary Sciences	207	3.136%

Figure 7.2. The distribution of research by *WoS* categories

Source: composed by authors using *WoS* database tools.

The first cluster consisted of 29 items, the second – 21 items, the third – 20 items, the fourth – 19, the fifth – 16, and the sixth – 5. The strongest keywords were artificial intelligence, machine learning, information, management, big data, and system. The distribution of the number of articles during the research period shows increasing relevance of the topic, with 186 articles in 2020, 236 – in 2021, 284 – in 2022, 308 – in 2023, and 38 – in the beginning of 2024, and 210 articles in average.

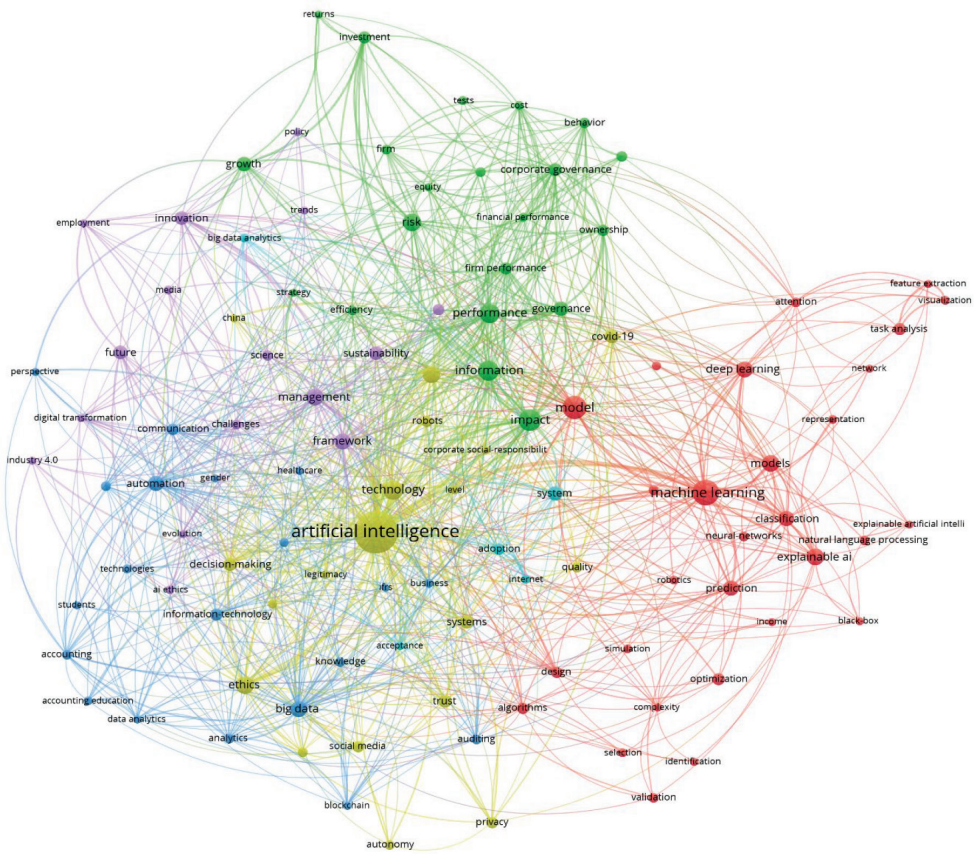

Figure 7.3. Analysis of keywords by the *VOSviewer*

Source: composed by authors using the *VOSviewer* tool.

Over the last five years, the amount of research in the field of AI in accounting has increased reasonably, with the highest increase in 2021, which was almost 27% compared to the previous year. In 2022, this number was 20%, and in 2023, it was 8%. No comparison can be made with 2024, as the number of articles represents only the number of articles published in the first two months of that year.

The following section reveals the traditional detailed analysis of articles, the results of the *RAYYAN* analysis, and the systematic analysis of the articles selected based on specific criteria.

7.2. Debate on Various Aspects of Artificial Intelligence in Accounting: Results of the Traditional Detailed Analysis of Literature

The traditional manual detailed analysis of the first ten articles (having both search keywords AI and accounting) out of 1,052 results from the WoS core collection shows that researchers have analysed various aspects of AI in accounting.

By analysing AI in accounting, some authors concentrated on educational issues. Leitner-Hanetseder et al. (2021) summarised their opinion that accounting would be subject to changes in the use of new (smart) technologies and big data, which will require different tasks and the upgrading of the qualifications as well as new forms of collaborations and interactions (in particular human-machine interactions). The authors identified eight core accounting roles in 2030, derived inductively during the Delphi study. In total, five out of the eight roles already exist, and three might be completely new in AI-based accounting. Authors systemised the main traditional roles in accounting and gave insights for their development: 1) transactions recorder – AI-based technology which extracts information from machine-readable digital data formats as a self-learning system, will post it to the correct account; humans will supervise the results and take care of exceptional cases the AI-based technology is not able to solve; 2) data and information manager – free data exchange standards will enable AI-based technology such as automated feature tools to collect and suggest internal/external and unstructured/structured data relevant for the task; humans will decide about the usage and/or supervise the selection of data; 3) data miner – AI-based technology (such as business intelligence tools) will use predictive analytics tools to analyse and recognises anomalies, interrelations, trends and patterns within big data; humans will be able to focus on major incidents; 4) dashboard designer – humans will design interactive dashboards with AI-based tools, which will meet the needs of the user in an iterative way in nearby real time; 5) advisor – AI-based technology will suggest data-driven decision options based on prescriptive analytics, humans will interpret the AI outcome and will understand the overall engagement process and have to weigh up options and will decide or communicate to stakeholders and advise due to their expert knowledge and experience. Leitner-Hanetseder et al. (2021) also revealed three new roles: 1) AI technology expert – humans will train and supervise AI-based technologies, such as a trainee, in a specific task and how to interact with humans to provide human and AI-based technology collaboration; 2) process manager – humans using AI-based will process mining tools identify processes for automation, select the relevant AI technology or component and make

sure that the collaboration of AI-based technology and humans work; 3) legal and ethical supervisor – humans will be responsible for guiding AI-based technology and monitoring whether the data-driven decisions made by humans meet legal and ethical requirements (Leitner-Hanetseder et al., 2021).

Holmes and Douglass (2022) provided insights from accounting professionals on the impact of AI adoption and the associated risks on the accounting profession. They conducted the survey and concluded that participants have an overall positive perception of AI and believe it will enhance their job performance by reducing repetitive tasks and the risk of human error. In addition, results show that the growth of AI technology will change the focus of accounting curriculums to include specialised computer skills. Besides, the authors concluded that skills in data management, data cleansing, and correcting inaccurate or incomplete data are valued more by industry and public accountants than accounting educators. They suggest that accounting programs should equip students to be life-long learners in accounting so they can grow with the changes in the profession. The authors have given an interesting opinion on relatively rapid changes in the main accounting functions, predicting the changes for the year 2030, although, from the perspective of the year 2024, we think that even if AI technology is used more and more, the changes will not come so fast as they require significant recourses. However, we should agree on the need for imperative changes in accounting programmes to help students prepare for the future reshaped by AI.

Interesting research on learning tasks in accounting textbooks was conducted by Stütz et al. (2022). The authors analysed 3,361 tasks from 14 accounting textbooks in terms of different characteristics with the help of AI. Their results indicated that in terms of process orientation, the tasks yielded above-average results compared to the other categories. The authors provide the opinion that the focus on business processes is seen as vital when it comes to the education of future accountants. By analysing the provision of real-world information in the tasks, the authors concluded that tasks lack a detailed and realistic description of occurring social processes, value processes, and cash flows. This lack can subsequently lead to learning difficulties and limit learners' ability to perform in the real work environment, as they cannot link the real world and the accounting world as part of their training. Although the descriptions of goods, cash flows, and social processes are both positively related to one another and to other categories (e.g., the identification of problems, translation, and operation within the accounting system), this could lead to an insufficient illustration of the connection between real business processes and their impact on corporate goals. Considering that accountants work with (digital) documents on a daily basis, textbook tasks do not foster the important skill of correctly handling them, with only 3% of the tasks containing realistic documents. The authors stated that the vast majority of the tasks do not contain a problem or clearly outline the problem, including potential solution paths, leading to the assumption that many tasks focus on the reproduction or application of knowledge, which indicates a knowledge/skill

gap in training, although identifying, analysing, and solving unstructured accounting problems are vital skills demanded by potential employers (Stütz et al., 2022). Besides, the authors outlined the ability to gather and assess information as a vital skill when educating future accountants. However, findings indicated that tasks do not (or in only a limited fashion) promote skills regarding the evaluation of information, as no task required assessing the relevance of included information, and most tasks did not require searching for additional information.

Regarding modelling competencies, research results indicated that accounting tasks split the complete modelling cycle into separate steps and mainly focus on applying formal accounting rules. In contrast, translating an economic phenomenon into accounting and interpreting and validating the solution is required less frequently. The authors provided an opinion that this focus on individual steps and separation of tasks does not allow learners to go through the complete modelling cycle. Thus, tasks in accounting textbooks focus on skills that allow accountants to acquire routine in dealing with accounting rules and concepts. Choosing the right concept for a business situation and validating the usefulness of the chosen concepts seem to be less important. The focus on operations within the accounting system is problematic and out-of-date, as many calculations and postings are performed automatically by modern accounting systems and, therefore, do not need the assistance of human accountants. Detecting mistakes and outliers and improving business processes means learners need to know if and how business situations affect variables such as a company's profitability or liquidity, so students need to interpret data and business situations rather than document them (Stütz et al., 2022). We can only agree with the opinion of Stütz et al. (2022) that the involvement of AI in the automation of routine accounting processes significantly changes accounting practice, which should also be reflected in educational programmes.

Some researchers analysed the application of AI in different accounting fields and issues related to its practical implementation. Norzelan et al. (2024) investigated the technological acceptance of AI by surveying 71 heads or representatives of the Shared Service Industry in finance and accounting units in Malaysia. Based on the results obtained from the study, the authors concluded that effort expectancy, social influence and facilitating conditions were not the crucial factors in predicting the technology acceptance of AI. Therefore, the authors suggested that the organisation should focus on the three factors: performance expectancy, attitude, and skill and technical capability to ensure future technology like AI can be embedded smoothly within the organisation. They thought AI could reduce routine tasks, streamline processes, and increase cost savings and efficiency by increasing the organisation's Return on Investment (ROI). Besides, individuals should also overcome their anxiety or fear toward AI and positively view AI's capabilities as AI technology has the potential to change society and significantly impact the quality of life by automating repetitive and time--consuming tasks. AI frees employees to focus on higher-value activities that can lead to job satisfaction, reduced stress and improved work-life balance (Norzelan et al., 2024).

Zhao and Wang (2024) explored the potential applications of ChatGPT in accounting and evaluated the benefits and challenges associated with its integration. The authors delved into various domains within accounting, including automation of routine tasks, financial and managerial analysis, auditing, taxation, and client interactions by examining real-world examples and synthesising existing research. They concluded that ChatGPT has the potential to lead to effective and streamlined accounting tasks and revolutionise accounting processes by bringing significant benefits to accountants. According to the opinion of Zhao and Wang (2024), ChatGPT can support auditors in fraud detection and flag potential anomalies to enhance the effectiveness of audit processes. ChatGPT can also aid in tax procedures to help interpret complex tax regulations and assist in accurate tax reporting. As a virtual assistant, ChatGPT can provide accounting guidance and explain accounting concepts to clients. The authors also emphasise that it is vital to acknowledge the challenges and risks associated with ChatGPT, including concerns about data quality and biases, user privacy and security, ethical considerations, and integration complexities.

Another team of researchers investigated the real ethical impact of AI on managerial accounting during both pre- and post-adoption stages by focusing on four types of stakeholders: developers, managers in charge of AI adoption, managerial accountants and regulators, and investigated ethical impacts on each group (Zhang et al., 2023). The authors conducted 47 interviews with companies adopting or using AI, an AI system developer, and regulatory agencies and discovered 15 stakeholders' ethical concerns at the pre- and post-adoption stages. They concluded that at the pre-adoption stage, the major ethical risks include data security, privacy, misuse, accountability of beneficiaries and AI vendors' competence. Since some of the impacts of AI on managerial accounting and decision-making can be observed immediately and others may be seen only after years of use, they further identified challenges at the post-adoption stage from two perspectives: 1) ethical issues in the use of AI and 2) long-term impacts of AI on employees and organisations. The first perspective focused on how ethical risks may influence managerial accountants' behaviours, such as gaps between user expectations of AI and actual use, transparency and trust of AI, bias, result distortion, and user competence. Zhang et al. (2023) stressed that these ethical risks may start from the trial operations of AI and continue throughout its use. As managerial accountants receive more training and user experience, ethical concerns may be reduced, such as expectation gaps and user competency. However, other concerns, such as bias, result distortion, and AI transparency and trust, may continue to exist. Long-term impacts of AI on employees and organisations also include AI accessibility, accountability of stakeholders when using AI, isolation, benefits and challenges, learning curve, and power over the user (Zhang et al., 2023).

Rawashdeh (2023) conducted a cross-sectional survey of accounting professionals to provide an in-depth understanding of how AI's integration in accounting contributes to job displacement, reshapes decision-making processes and reverberates across economic and social dimensions. The author revealed the

multifaceted consequences that arise from AI's integration into the accounting field, such as a cascade of impacts on decision-making, economic frameworks, workflow methodologies and societal dynamics. Rawashdeh (2023) argued that the assimilation of AI within accounting practices precipitates job displacement and shifts in work methodologies. AI's prowess, enabling the automation of erstwhile human-centric tasks – spanning repetitive chores, intricate data analysis and pivotal decision-making – paves the way for such displacements. From the perspective of employers, the economic calculus may tilt towards AI adoption to pare down expenses, elevate productivity and amplify profitability. Besides, research results showed a positive association between AI incorporation in accounting and social dislocation stemming from job displacement (Rawashdeh, 2023).

Le Guyader (2020) analysed how the "FAS133-AI" experience has become a model for how accounting can use AI solutions, and regulators may demand them. The author concluded that the training regime for new AI functionality and the new AI itself creates the unintended risk that the staff will be trained in AI but not in the concepts, rules, and details of the underlying accounting standards. Where a standard such as FAS133 brings capital markets notions into the accounting solution, and only a subset of accountants gain the requisite finance training, the AI solution decreases the need to acquire that extended expertise. Le Guyader (2020) gives insights into the challenges to the profession from the emergence of AI, including the need for accountants to become experts in AI and related technology as users. The author emphasises the importance of the capacity and willingness of accounting professionals to educate their members on the underlying accounting rules the AI solution is meant to address (Le Guyader, 2020).

Other scholars analysed AI adoption in different sectors and countries. Monteiro et al. (2023) identified the intensity of AI adoption in the manufacturing industry and internal control system quality as critical factors for the accounting information system quality. Based on a sample of Portuguese companies' managers, the authors found that the intensity of AI adoption has a strong connection with the manufacturing industry besides, manufacturing companies, because they gather large amounts of data and complex production data, adopt AI to transform complex data into actionable and insightful information. Researchers concluded that the intensity of AI adoption contributes positively to the internal control system quality and that AI improves the quality of accounting information systems and internal control systems (Monteiro et al., 2023). The authors suggested that AI adoption should be part of the company's strategy, as it reduces accounting errors committed by humans and improves the effectiveness and quality of accounting information systems and, consequently, the internal control system. Researchers also found that internal control system quality favours the relationship between the intensity of AI adoption and accounting information system quality (Monteiro et al., 2023).

Lee and Tajudeen (2020) investigated the use and impact of AI-based accounting software among organisations in Malaysia by performing face-to-face interviews

with representatives from nine organisations using AI-based accounting software. The authors provided results on various adoptions of AI-based accounting software across organisations, such as tools to deposit document images, capture invoice information automatically, monitor invoice approvals, manage risks, and track users' activities. Researchers suggested that AI-based accounting software has accelerated productivity, improved efficiency, enhanced customer service, supported flexible working styles, increased process governance, and saved manpower (Lee and Tajudeen, 2020). The analysis of the adoption and application of AI in practice also reveals the tendencies of the huge impact of AI on different areas of accounting and the need to be prepared for the changes.

In summary, some researchers examined how AI changes the accounting profession, roles, tasks and responsibilities, and its role in displacing jobs. Other researchers have focused on assessing how AI is accepted by finance leaders, accounting professionals and industries, how the technology affects efficiency, decision-making and ethical considerations in accounting practice, and its impact on internal controls and information quality. The authors show how AI changes the landscape of accounting education, requiring new skills, learning approaches, and educational requirements. Researchers also consider the interaction of AI with established accounting standards, such as GAAP's FAS133, and highlight the evolving nature of financial reporting and compliance in the age of AI.

Analysis of the first 10 articles revealed the importance of AI implementation in practice, its benefits, factors, ethical issues, and impact on shaping the future of accounting.

7.3. Artificial Intelligence in Accounting Business and Education: Results of Systematic Literature Review

The process of literature analysis was continued by narrowing the search using the keywords: "education" and "business" and the function of the *WoS* database "search within results". The search yielded 51 articles analysed using the *RAYYAN* literature analysis tool. The results of the screening are shown in Figure 7.4.

Under the *RAYYAN* tool, all 51 articles were screened. One source was removed as a book with no access, as were 4 other articles. 24 sources were excluded, with reasons given in Figure 7.4. 22 articles were assessed manually. Table 7.1 shows the results of the systematic analysis of the articles according to the main criteria.

Figure 7.5 shows the main emphasis and research objects of the 22 analysed articles.

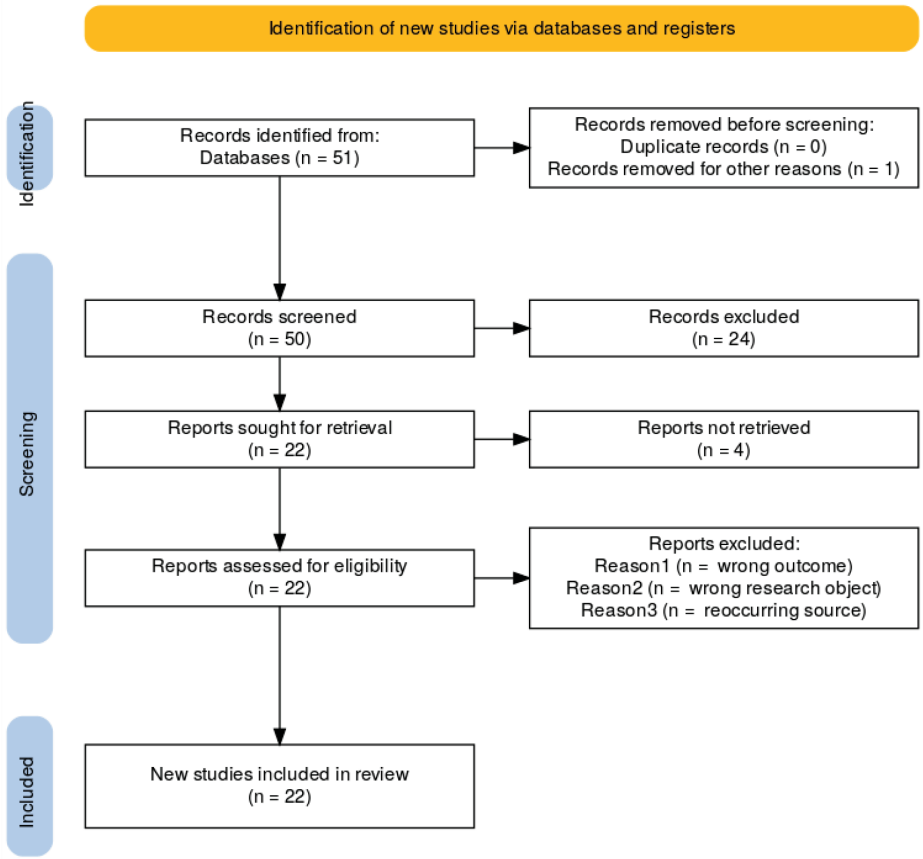

Figure 7.4. Literature analysis results by the PRISMA

Source: composed by authors using the *RAYYAN* tool.

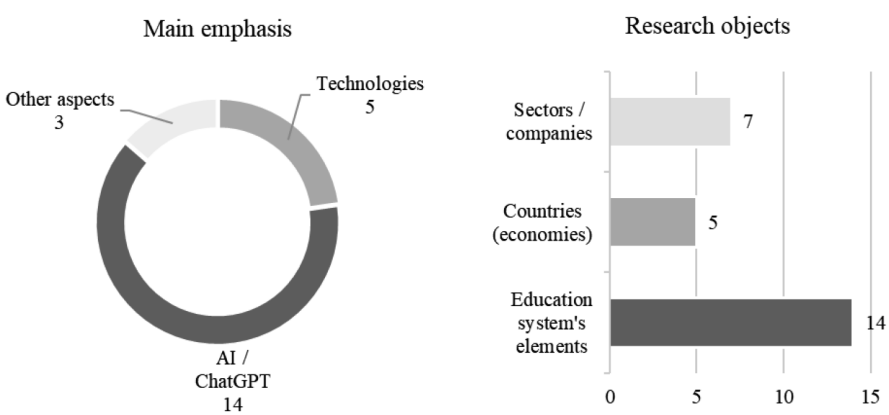

Figure 7.5. The main emphasis and research objects of the analysed literature

Source: own presentation.

Table 7.1. Results of the systematic literature analysis (*n* = 22)

1) Onyshchenko et al. (2022), Industry 4.0 and Accounting: Directions, Challenges, Opportunities	
Main results	Authors suggest that technology will not supplant accountants, but on the contrary, will help to enrich their knowledge, skills and abilities; will set aside time for accountants to analyse and manage the company's activities; make it easier for accountants to perform routine actions and operations. The evolution of digital transformation in the accounting information system will accelerate the accountant's work for more accurate, efficient and real-time reporting.
Research methods and data	A qualitative research design, the method of indirect observation, causal analysis and predictive synthesis, induction and description, critical analysis and comparison of analytical reports, surveys, research proposals for literature review and desk research of current business press reports, professional reports, Industry 4.0 technology company webpages, and modern accounting technologies, 64 economies (countries).
2) Ng (2023), Teaching Advanced Data Analytics, Robotic Process Automation, and Artificial Intelligence in a Graduate Accounting Program	
Main results	The results suggest strong evidence of student learning related to the course learning objectives that give insights for preparing students and academic accounting departments to develop strategies to integrate data analytics and emerging technologies into the curriculum.
Research methods and data	A statistical analysis of precourse/ postcourse student reflections and feedback surveys to evaluate a quality assurance initiative.
3) Damerji and Salimi (2021), Mediating Effect of Use Perceptions on Technology Readiness and Adoption of Artificial Intelligence in Accounting	
Main results	The findings from the study indicate that technology readiness has a significant influence on technology adoption. However, mediation analysis using hierarchical regression showed that the relationship between technology readiness and technology adoption of AI is affected by both perceived ease of use (PEOU) and perceived usefulness (PU).
Research methods and data	An online questionnaire, hierarchical regression, HEIs students.
4) Qasim et al. (2022), Embracing Emerging Technologies and Artificial Intelligence into the Undergraduate Accounting Curriculum: Reflections from the UAE	
Main results	The study explores the extent to which the current accounting curriculum in the UAE reflects the current digital transformation in the country.
Research methods and data	Analysis of government initiatives toward AI transformation, adoption of AI, Blockchain Technology (BT), and Data Analytics (DA) in corporations and government agencies in the UAE and existing accounting curricula.
5) Онешко et al. (2023), Accounting and Financial Reporting in the IT Sphere of Ukraine: Opportunities of Artificial Intelligence	
Main results	The research has accurately scrutinised AI efficacy in elevating the precision of financial reporting, even in the face of disruptive crises. The empirical findings of this study have yielded illuminating revelations, underscoring the unequivocal positive influence of AI on the accuracy of financial reporting and its integral role in crisis mitigation.

Table 7.1, cont.

Research methods and data	The intricate application of AI within the context of Ukraine's IT sector, with a specific focus on accounting and financial reporting, integrates Bayesian analysis and repeated measures of ANOVAs; the dataset consists of 113 participants.
6) Liao et al. (2024), Hyperbole or Reality? The Effect of Auditors' AI Education on Audit Report Timeliness	
Main results	Results show that auditors with AI education can shorten annual audit report times by using programming, applied technology, and logical-thinking skills, thereby enhancing audit report timeliness. Auditors' AI educational background and CPA experience are complementary in mitigating audit report lag, particularly in companies with higher client portfolio risk.
Research methods and data	Descriptive statistics, correlation analysis, an individual-level auditor setting to investigate the role of AI education in audit report timeliness, and manually collected data on auditors with AI educational backgrounds comprising 8201 company-year observations of A-share listed companies in China between 2014 and 2020.
7) Ahmed et al. (2022), Motivators and Barriers of Artificial Intelligent (AI) Based Teaching	
Main results	The findings demonstrate that schools must equip teachers with the resources, support, and recognition they need to adopt AI-based pedagogies. Furthermore, higher education institutions (HEIs) must offer their academic members adequate resources, including money and technological equipment. According to studies, self-motivation is the least influential factor in university instructors' adoption of AI. Teachers and administrators who are overworked are less likely to be willing to experiment with new technologies. They place greater importance on public recognition and educational benefits than personal development. Teachers may be incentivised to utilise innovative and novel teaching methods through financing programs or other incentives.
Research methods and data	The study is based on a questionnaire; pair-wise comparisons using a statistically significant sample of 218 Malaysian university professors.
8) Alshurafat et al. (2023), Factors Affecting Accounting Students' Misuse of ChatGPT: An Application of the Fraud Triangle Theory	
Main results	The results show that all fraud triangle factors are significant determinants of student academic dishonesty and student misuse of ChatGPT. Based on the findings of this research, students indicate that ChatGPT presents an accessibility to cheat, as it caters to the three components of the fraud triangle: opportunity, rationalisation and pressure. Therefore, educational institutions should adopt and enforce strict policies and guidelines on academic integrity, while educators should incorporate innovative and effective teaching strategies to promote a deeper understanding of the material.
Research methods and data	Data on how accounting students used ChatGPT to cheat was acquired from 238 accounting students in Jordanian public universities over two months through previously tested and validated questionnaires. The main tool for gathering data was a questionnaire distributed online using Microsoft Forms; statistical analysis.
9) Li and Zhao (2022), Research On the Influence of Artificial Intelligence Technology with Web 3.0 on Accounting Education and Its Countermeasures	
Main results	Results show that accountants must establish the concept of lifelong learning, constantly improve their learning ability, and constantly update their knowledge structure to meet the requirements of accounting practice reform. On the one hand, the

	education sector should guide students in establishing the concept of lifelong learning, not only because the economic business and accounting standards are constantly changing but also because the development of AI technology requires students to have the quality of lifelong learning. Accounting education should improve students' ability to innovate and self-learn and enable them to develop lifelong learning methods and abilities.
Research methods and data	The study investigates the accounting industry as an example, discusses the application of AI in accounting practice, analyses its impact on the reform of accounting education, and finally proposes countermeasures and suggestions for accounting education to deal with technological challenges with blended learning for increasing student retention and engagement in an E-learning environment.
10) Selamat and Ngalim (2022), Putra Salamanis Board Game: The Game of Bookkeeping for Fundamental Financial Accounting Learning	
Main results	The paper introduces the Putra Salamanis game developed by the authors, inspired by the well-known board game Monopoly, as a suitable board game for teaching financial accounting fundamentals. In this game, business transactions are recorded based on the double-entry rule. This requires students to recognise the five accounting elements of assets, liabilities, equities, revenue, and expenses, which are vital in accrual basis accounting.
Research methods and data	A pilot group of students who engaged in the game provided positive feedback, implying that the game facilitated students' learning and understanding of the basic concept of double-entry bookkeeping and accrual accounting.
11) Hadi and Abdel-Razzaq (2024), Promoting Sustainable Learning Among Accounting Students: Evidence from Field Experimental Design	
Main results	Significant results were found throughout the different academic classifications (seniority): freshman students, junior students and senior students. Further, differences in the mean scores for freshman and junior accounting students were different between the male and female students, indicating that both male and female senior students' attitudes toward sustainability in accounting education were higher than those of male and female freshman and junior accounting students. The study concluded that students achieve an adequate understanding of sustainability in accounting education related to the relativism category of the Perry model of intellectual development.
Research methods and data	The study used a quantitative research design where data were collected at a single point in time. Further, an independent sample *t*-test, one-way ANOVA and factorial design were performed on 132 responses conveniently collected from accounting students in the College of Business Administration (COBA) at Prince Mohammad Bin Fahd University (PMU) in Al Khobar, Saudi Arabia.
12) Hu et al. (2021), Construction of an AI-Driven Risk Management Framework for Financial Service Firms Using the MRDM Approach	
Main results	The results indicate that the improvement priority, which runs in the order of (a) AI algorithm model, (c) AI regulatory and compliance, (d) AI conduct, and (b) AI technology based on the magnitude of the impact, can effectively improve the performance of AI-driven risk management for financial service firms.
Research methods and data	This study proposes a fusion multiple rule-based decision-making (MRDM) approach that integrates a rule-based technique into MCDM techniques to help decision-makers choose the optimal model for achieving aspiration-level effects in a risk control strategy.

Table 7.1, cont.

13) De Villiers (2021), Seven Principles to Ensure Future-Ready Accounting Graduates – A Model for Future Research and Practice	
Main results	The study derived the seven Cs model, which includes critical, conceptual thinking and the spirit of enquiry; complicate, grapple and fail; create, innovate and experience; concise communication; collaboration; consciousness, respectfulness and ethical fibre; and curiosity, lifelong learning and specialised generalists. Accounting graduates must be inquisitive, agile, self-directed, lifelong learners who can think for themselves and steer their careers.
Research methods and data	The seven principles are derived from an extensive literature review and qualitative data analysis from focus groups, thought leader discussions, and semi-structured interviews with thought leaders and workshops.
14) Prokofieva (2023), Integrating Data Analytics in Teaching Audit with Machine Learning and Artificial Intelligence	
Main results	The study reveals the conceptual framework of audit analytics and guides on implementing it in teaching audit. The focus of the provided implementation is on domain-specific knowledge and skills in auditing. Data analytics supplements and automates auditing tasks and positively affects the acquisition and retention of auditing--related knowledge and skills. The suggested implementation guidance provides a roadmap for integrating data analytic competencies into the accounting curriculum to enhance students' learning and improve employability and graduate outcomes in the rapidly changing business environment.
Research methods and data	The study conducted the process model methodology by developing a procedural meso-level model that focuses on guiding end-to-end flows of tasks in audits applicable to real-world audit engagements. The process modelling results were evaluated in the focus group with accounting academics and audit professionals. The hybrid approach of curriculum development and implementation was evaluated in a series of workshops and a survey with participants (students).
15) Domini et al. (2022), For Whom the Bell Tolls: The Firm-Level Effects of Automation on Wage and Gender Inequality	
Main results	The results show that within-firm wage inequality is a pervasive phenomenon in the French economy; most wage dispersion in France is accounted for by differences among workers belonging to the same firm rather than by differences between sectors, firms, or occupations; the increase in wages brought about by the adoption of automation and AI is enjoyed by all workers in the adopting firm, irrespective of their initial wage or gender; spike events related to the adoption of automation- and AI-related capital goods are not followed by an increase in within-firm wage inequality or gender wage inequality. Instead, wages increase by 1% three years after the events at different percentiles of the distribution.
Research methods and data	An event-study approach on a sample of firms importing automation- and AI-related goods was used for the research. The dataset contains data from all French firms with employees over the 2002-2017 period, obtained by merging different administrative sources, using the unique identification number of French firms, a dataset by the French customs office, and a confidential database provided by the French national statistical office.

16) Strzelecki and ElArabawy (2024), Investigation of the Moderation Effect of Gender and Study Level on The Acceptance and Use of Generative AI by Higher Education Students: Comparative Evidence from Poland and Egypt	
Main results	The findings show that performance expectancy, effort expectancy, and social influence significantly influence behavioural intention. Furthermore, when considered alongside facilitating conditions, behavioural intention influences actual user behaviour. The results augment comprehension of technology acceptance in the context of AI tools and provide valuable input for formulating strategies that promote the effective incorporation of ChatGPT in higher education. The study underscores the need for effective awareness initiatives, bespoke training programmes, and intuitive tool designs to bolster students' perceptions and foster the broader adoption of AI tools in education. The integration of ChatGPT in HEIs holds the potential to deliver personalised and relevant learning experiences to students, streamline administrative procedures and advance research and community engagement. However, it is essential to employ ChatGPT ethically, considering the need to develop individual and institutional capabilities.
Research methods and data	The study relies on data collected from six universities in two countries and is assessed through descriptive statistics and structural equation modelling techniques. It also takes into account participants' gender and study level. In the pilot study, 36 students were surveyed and requested to provide feedback on the comprehensibility of the scales. After the pilot study, the survey was administered to students at the universities located in Katowice, Poland, and Cairo, Egypt. The survey remained accessible for one month.
17) Tiron-Tudor and Deliu (2021), Reflections on the Human-Algorithm Complex Duality Perspectives in the Auditing Process	
Main results	The results debate the complex duality between algorithms and human-based actions in the institutional settings of auditing activities by highlighting the actual stage of algorithms, machines, and AI emergence in audits and providing real-life examples of their use in the audit. Furthermore, they emphasise the strengths and weaknesses of algorithms compared to human beings. Based on the results, a discussion on the human-algorithms interaction from the lens of the Human-in-the-Loop (HITL) approach concludes that the Auditor-Governing-the-Loop may be a possible scenario for the future of the auditing profession.
Research methods and data	The research uses a qualitative reflexive thematic analysis, considering the academic literature, professional reports, and websites of the "Big Four" audit firms and internationally recognised accounting bodies. The authors conducted a reflexive thematic analysis of scientific literature and professional technical reports issued by large audit firms, international standards setters and organisations.
18) Dabbous and Boustani (2023), Digital Explosion and Entrepreneurship Education: Impact on Promoting Entrepreneurial Intention for Business Students	
Main results	This study proposes a model to investigate entrepreneurial intentions among business students in higher education in Lebanon. The model includes five factors that affect entrepreneurship intentions: entrepreneurial education, performance expectancy of AI solutions, risk aversion, social support, and business climate. Furthermore, it assesses the role of perceived behavioural control as a mediator. The estimation results highlight that the performance expectancy of AI and entrepreneurship education can influence the intention to become an entrepreneur by enhancing the perception of the capacity to create and operate a new venture. The findings highlight the need to account for entrepreneurship education and AI development when analysing entrepreneurial intentions.

Table 7.1, cont.

Research methods and data	350 questionnaires were sent by e-mail to a dataset of students who acquired a business education at a well-known university in Lebanon. 223 surveys were included in the sample after removing unengaged respondents and questionnaires with missing values.
19) Leander and Burriss (2020), Critical Literacy for a Posthuman World: When People Read, and Become, with Machines	
Main results	The uses of AI and developing a critical literacy engaged with AI offers newly complicated opportunities to reconsider the relations of literacy (and media); to identify this transformation, humanist perspectives on texts, images and identities need to enter into a new circulation with posthumanist perspectives in order to remain relevant for current techno-social relations. Authors imagine a posthuman critical literacy that moves humanity beyond critique and toward transformation – toward a more socially just and ethical world.
Research methods and data	Literature analysis, interviews with professionals who use forms of AI extensively in their work.
20) Hu et al. (2023), Governance of Artificial Intelligence Applications in a Business Audit via a Fusion Fuzzy Multiple Rule-Based Decision-Making Model	
Main results	Research results show that the priority dimensions for improvement are AI application strategy, AI governance, data infrastructure, data quality, and human factors. This research proposes a systematic and reliable improvement project for accounting and auditing professions when they adopt AI in their internal audit process. Motivated by a model ensemble, a comprehensive decision framework established herein integrates FCM, DRSA, FDEMATEL, INRM, FDANP, and modified VIKOR.
Research methods and data	This study employs a questionnaire, which was developed in three major steps. In the first step, the authors followed the guidance on the AI internal audit framework (IIA 2017a, b, c, d) and extended this framework by reviewing related literature. From detailed evaluation, discussion, and literature reviews, they summarised the collected data, represented them in a hierarchical structure, and set up four dimensions and 23 criteria. The authors invited ten chief audit executives or heads of internal audit departments and 8 senior engineers of enterprises with imported AI technology from Guangzhou and Shenzhen to complete the preliminary questionnaire to assess AI in China's internal auditing industry.
21) Ullal et al. (2020), The Effect of Artificial Intelligence on the Sales Graph in Indian Market	
Main results	The results show that disclosure of the identity of AI reduces purchase chances drastically; purchase rates dip and calls are disconnected when the identity of AI is revealed as Indians perceive AI as less capable and have less knowledge, which cannot understand human feelings and requirements. The research outcomes reveal that the effectiveness of AI is the same as that of experienced salesmen and 2.7 times better than inexperienced salesmen closing sales calls. The sales graph experienced a dip of over 86.23% when it was revealed to the customer that the interface was with the machine, not humans, reducing the call's duration substantially. The results show that Indians do not believe in AI and still prefer human interface as they do not trust machines over human emotions. The effectiveness of AI has drastically reduced despite its superiority over humans in various aspects. The authors identify the strategies to overcome the trust deficit among Indian customers. The outcomes show how AI can be used and how marketing could be done using AI in conservative markets such as India.

Research methods and data	The experiment was conducted by one of the leading Chennai-based data collection and experimentation agencies, ranked number 1 in India with over 7 million customers. All the customers were online buyers who used e-commerce portals frequently and were active social media users. 4,500 responses were collected after filtering out all the unanswered or connected calls. The company has software to make calls and provide services that allow customers to have conversations in natural settings. The machines here, backed by AI, are well-trained to perform the routine tasks of experienced salespeople.
22) Papakonstantinidis et al. (2024), Embrace or Resist? Drivers of Artificial Intelligence Writing Software Adoption in Academic and Non-Academic Contexts	
Main results	Findings yield insights into non-academic writers' readiness and implications of AI writing software (AIWS) adoption. Business non-academic professionals view AIWS as a tool for efficiency and content quality, while writers in academic contexts express concerns about biases, manipulation, and job displacement. These findings highlight the complex interplay between cognitive factors, behavioural outcomes, and age in accepting and utilising AI writing software. The stronger direct effect observed among academics suggests that cognitive factors primarily drive their acceptance of AI writing tools. On the other hand, professionals' acceptance is influenced by affective factors mediated by cognitive factors. Additionally, the moderation effect of age further emphasises the need to consider age-related differences in adopting AI writing software, particularly among professionals.
Research methods and data	The study adopted a quantitative methodological approach. A comprehensive survey comprised 22 questions pertaining to focal constructs from the NCGAS scale and respondent characteristics. The three scale dimensions typically included in a TAM questionnaire were used in the construction of this survey: cognitive (COG), affective (AFF), and behavioural (BEH). In a questionnaire, the cognitive dimension focuses on individuals' beliefs and perceptions regarding the technology being studied. A survey of 219 participants included academia and business respondents.

Source: composed by references provided in the table.

7.4. Conclusions

The analysis of the articles shows the main trend of the importance of AI or other technological advances, their impact on business practice, and, most importantly, the need to adapt educational curricula to changing conditions. The study's results and the business implications highlight the critical role of AI in revolutionising accounting and business operations. The integration of AI enables improved decision-making, predictive analytics and operational efficiency. This paradigm shift means that businesses and accounting professionals must adapt to embrace AI-driven methodologies to remain competitive and efficient. Regarding educational implications, the findings highlight the urgent need to revamp educational curricula. Integrating AI and other technological advances into the preparation of the profession requires an education system that is responsive and adaptable to these changes. This means not only incorporating AI knowledge and skills into curricula, perhaps even

changing the assessment strategy but also preparing students for an ever-changing economic and technological environment.

Future research should aim to assess the effectiveness of revised curricula incorporating AI and technology-focused subjects and assessment strategies. Subsequent studies could evaluate the impact on student preparedness for the modern workplace and their ability to innovate within AI-driven business and accounting environments. Studies that observe how AI implementation affects business performance, accounting accuracy, and decision-making processes over time can present the challenges and benefits of AI implementation. Additionally, it is crucial to evaluate the ethical considerations and societal implications of deploying AI in business and the education field of accounting.

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Chapter 8

Regulatory Frameworks for the Use of Generative Artificial Intelligence – Challenges for Higher Education

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Artificial Intelligence (AI) is one of the most critical challenges shaping today's reality. The use of AI by students and academics is a reality. The survey – "Technology through the eyes of the student" – conducted by *Digital Care* indicates that 68% of students plan to use generative AI tools during their studies, mainly for language translation, organising their work, creating presentations, and writing their final and dissertation papers. More than 60% of students relate to the use of AI positively or strongly positively, and only 10% negatively (Reszczyński, 2023). An analysis of the regulations and guidelines for Polish students and academics on the use of generative AI tools revealed a research gap in this area. Higher education institutions are currently in the early stages of implementing recommendations and guidelines. This chapter may be an important voice in the discussion on this topic. The aim of the article is to analysis of regulations concerning the use of generative AI in education and teaching at selected Polish universities and to identify recommendations for the use of AI in the higher education system, with particular reference to European Union regulations.

The chapter's content is divided into the following parts: section 8.1 reviews the regulatory frameworks for using AI tools in higher education at the EU and national levels and analyses the existing guidelines and recommendations in 9 higher

education institutions in Poland; section 8.2 discusses the importance of AI from the perspectives of students, academic staff, and university administration; section 8.3 includes recommendations directed at the academic community and emphasises the need for creation of good practices at the ministerial level concerning the use of AI in higher education.

8.1. Review of Regulations, Guidelines and Recommendations Regarding the Usage of Artificial Intelligence in Higher Education

AI poses a significant challenge for the educational field in the coming years. A study carried out in a report by the PARP (*Polish Agency for Enterprise Development*) analysed the frequency of occurrence of the words "sztuczna inteligencja"[1] and "artificial intelligence" in a Google search in connection with the word "edukacja"[2] or "in education". It turned out that these associations occur far more frequently than associations of the words "artificial intelligence" with other words, e.g. in logistics, medicine, etc. (PARP, 2023, p. 3). In addition, it was pointed out that interest in this topic is strongly growing.

Therefore, regulating AI in an economic environment has become a necessity. The European Parliament, as part of its digital transformation strategy, wanted to regulate AI, ensuring better conditions for its development and use since many benefits (better medical care, 'green' transport, more efficient production) have been noted. In 2021, the European Commission developed the first EU legislative framework for AI. They also highlighted the risks. The framework analyses and classifies AI systems according to risk levels. The level of risk determines the number of obligations associated with the use of AI. Unacceptable risk systems are identified, e.g. cognitive-behavioural manipulation of humans – posing a real risk to humans. Interestingly – education and vocational training were placed in a high-risk area, along with the management and operation of critical infrastructure or law enforcement.

In March 2024, the European Parliament adopted the Artificial Intelligence Act after negotiations with the Member States. It mainly aims to protect fundamental rights, democracy, the rule of law and the environment from high-risk AI systems. At the same time, the regulation supports innovation while mainly focusing on potential risks (*Artificial Intelligence Act,* 2024).

AI is a broader term than content-generating AI (GenAI). The following chapter addresses issues mainly related to content generators, e.g. ChatGPT, YouChat or Wordtune, which are widely used in education. Text generators are so-called language models that use machine learning in their operation. Text creation is based on a command (prompt) the user imposes. The more specific the command, the faster the generator can write high-quality content. The European Parliament points to

[1] 'Artificial intelligence' in Polish language.

[2] 'Education' in Polish language.

transparency in the use of these tools – revealing that the content is generated by AI and ensuring that it does not contain illegal content.

A review and analysis of existing regulations, guidelines and recommendations for the use of AI by students and academics testifies to the preliminary stage of this process. One may risk stating that the regulatory frameworks for the potential use of AI in Polish higher education institutions do not fully meet the needs of its users.

In order to confirm the above hypothesis, the guidelines and recommendations for the use of AI at universities in Poland were reviewed[3]. The vast majority of universities in Poland do not have any regulations in this regard. Table 8.1 presents the guidelines and recommendations from 9 higher education institutions.

Table 8.1. Guidelines and recommendations for the use of AI in selected universities in Poland

Provision to GenAI usage	Reference to final assignments bachelor's thesis master's thesis	Guidelines and recommendations	Length
1	2	3	4
University of Warsaw			
YES	YES	■ providing regular training and discussions on the use of AI ■ raising awareness of data protection and copyright protection	4 pages
Warsaw School of Economics			
NO, there is no explicit provision for this, although the text may indicate it.	NO, but it is stated that the guidelines apply to written work.	■ There are no literal recommendations, but there are guidelines in the following scheme: PERMITTED, NOT PERMITTED, broken down into 10 areas: ideation, knowledge acquisition and literature review, writing, text operations, graphics creation, programming, data analysis, economic and mathematical modelling, AI as a research subject, reporting on the use of AI	5 pages
Kozminski University			
YES	NO, refers to the education process in general	■ promoting openness with critical thinking ■ indicating the importance of transparency in the technologies used ■ promoting diversity of sources ■ emphasising the necessity of increased awareness about AI errors ■ indicating the need for content detectors and random checking of papers for AI use ■ emphasising students' independence in the thesis writing process	1 page

[3] The review took place in February 2024.

Table 8.1, cont.

1	2	3	4
Poznań University of Economics and Business			
YES	NO	■ addressing the openness to the use of digital technology ■ indicating the need for increased awareness of potential risks ■ emphasising the subject of sensitive data and copyright	1 page
University of Lodz			
YES	NO	■ recommending the use of a variety of sources ■ highlighting the possibility of AI making mistakes ■ emphasising the issues of legality, protection of personal data, right to privacy ■ indicating the importance of transparency, i.e. marking content sourced through content generators, ■ indicating the need for using content detectors, ■ highlighting personal responsibility for the content generated	3 pages
University of Gdansk			
YES	NO	■ emphasising openness and a critical approach ■ indicating the importance of transparency in the use of AI ■ promoting respect for ethical principles and copyright, ■ indicating personal responsibility for the content generated, ■ disclosing when the content generated is not authored by the student/researcher ■ verifying the content by random use of content detectors ■ recommending continuous improvement of skills in AI and promoting content about AI	1.5 pages
Adam Mickiewicz University Poznań			
YES	NO	■ indicating the transparency importance by disclosing the content generators used, e.g. in the introduction of the work ■ emphasising independent writing in accordance with the requirements of the Act: Higher Education and Science Law of 20 July 2018 ■ enabling verifiability of AI usage by applying content detectors ■ emphasising the autonomy of the lecturer, who can determine his/her own rules for the use of AI	3 pages

1	2	3	4
University of Szczecin			
YES	NO	■ identifying areas of opportunity for the use of AI, such as the creation of teaching materials, content translators, automation of repetitive tasks, and support for scientific research ■ identifying the risks of using AI, such as bias, privacy, data security, manipulation ■ emphasising the autonomy of the lecturer, who may not allow students to use AI.	2 pages
Wroclaw University of Economics and Business			
YES	2 separate regulations – for theses and didactics	■ emphasising openness, responsibility and critical thinking ■ highlighting ethics and transparency ■ stressing the lecturer's autonomy	1 page

Source: own elaboration based on documents of individual universities.

After summarising the above guidelines and recommendations, two approaches can be distinguished:

- a more restrictive and critical approach towards the use of AI tools (mainly Warsaw centres),
- a more liberal approach – treating AI tools as new sources of knowledge (economic universities).

The critical approach points out explicitly what is allowed or not allowed and emphasises the importance of verification with content detectors and random checking of papers. The liberal approach emphasises openness and critical thinking on the part of the students and relies on the autonomy of the lecturer. Most positions jointly sensitise data security, privacy and student autonomy. Transparency and ethics in the use of AI tools are emphasised. Most universities also promote awareness of the existing threats related to the use of AI tools, such as AI hallucinations, biases, and errors.

Other countries are similarly attempting to regulate the use of AI in higher education. In the UK, unlike in Poland, where each university develops its own guidelines – an association of 24 universities has developed common guidelines on the use of AI in education (including Oxford, Cambridge, Bristol, and Durham). These are relatively general guidelines where the universities declare that they will:

- support students and staff in acquiring AI skills,
- adapt teaching and assessment to the use of AI,
- seek different access to AI tools,
- share good practices as technology evolves and is applied to education.

The association of these universities believes that it is better to teach the ethical and responsible use of AI than to apply prohibitions of various kinds. Students and teachers must continuously improve their skills in using AI, not least to be aware of its errors, inaccuracies, distortions or biases (Cimerman, 2023).

8.2. The Importance of Artificial Intelligence in Education

AI should enhance the learning process. Its importance can be considered on several levels. AI can be an opportunity to make teaching and learning more effective.

From the perspective of students, the main effect of implementing AI for learners is an increase in their motivation and engagement in the learning process (Xia et al., 2022). Students can use AI tools in the educational process, and its potential to personalise learning (now so often emerging in educational trends) should be highlighted. Tailoring learning to individual needs is difficult with the traditional form of teaching. The current system is rather oriented towards standardising the learning process. AI can increase the intensity of testing it deems to need improvement or reduce the number of tasks in areas less critical to the individual student's needs. Another advantage is effective feedback, which is not always possible in a traditional group. AI can effectively identify knowledge and skill deficits. Based on collected historical data, it can produce personalised feedback. This assumes that such information is objective and honest. Unfortunately, we must all be aware of the imperfections of AI or even its incorrect programming, which can lead to discriminatory or biased information.

From the perspective of academic staff, AI can assist them in assessing student work, making this process fully or partially automated. For the time being, this is relatively easy at the test level. Qualitative assessment is much more complicated. Entering final grades or filling in various reports can also help. AI can also help prepare teaching materials (e.g. presentations) or tests. Lecturers can use AI to simulate practical tasks, such as using virtual reality (VR), augmented reality (AR) or educational games. Supporting university teachers can also apply to their research, but this is not the subject of the following article.

From the perspective of university administration, AI algorithms can be used to evaluate the work of lecturers or administrative staff, predict trends or risks, and reduce the bureaucratic work of university staff.

AI will bring about lasting change at every level of education. This should not be overlooked, and we should continue to teach as if this technology did not exist. Additionally, research conducted in this area clearly indicates that the use of AI influences interest in learning and improves teaching competence by providing inspiration and promoting self-reflection (Aldeman et al., 2021; Lin and Chang, 2020). Research indicates that most students and teachers use AI tools and believe that ChatGPT, among others, will be indispensable for success in studies and work.

At Swedish universities, results from a survey of 6,000 students confirm positive attitudes towards AI, with students pointing to chatbots as a source of knowledge and inspiration, calling them tutors, mentors or teachers. The vast majority of respondents used ChatGPT to summarise their lectures or texts they were reading. Translation tools, speech-to-text transcriptions, writing support tools, and text enhancement tools are also very popular. Interestingly, most students could not answer whether there were any rules or guidelines governing the use of AI at their universities (Newseria, 2023; Walton Family Foundation, 2023; Welding, 2023;).

8.3. Conclusions

The use of AI tools in universities has become a reality. It is a technology that is highly trusted, especially among young people. Poles studying at Europe's top universities (University of Warwick, London School of Economics, Universitet van Amsterdam, Warsaw School of Economics are not afraid of the challenges of AI and are optimistic about the future in terms of using AI tools. Almost six out of ten students cannot imagine everyday life without using AI (Rzeczpospolita, 2023).

Additionally, it is intriguing that students are unaware of any guidelines or rules regarding AI use. A survey conducted in February 2024 found that students did not seek or know anything about regulations or guidelines to govern the use of generative AI at their university.

Universities face a significant challenge in raising awareness of the risks that AI can generate. On the other hand, students and lecturers need to be supported in the use of these tools. Systematic training is needed for teaching staff, who should emphasise and accentuate critical thinking on the part of the student, combined with openness to new technologies.

To summarise the considerations, one can refer to the recommendations developed by the team of researchers from the Silesian Centre for Engineering Technology Law and Digital Competence CYBER SCIENCE. These are general recommendations that could be a starting point for universities in Poland. The most important of these are (Uniwersytet Śląski w Katowicach, 2023):

- openness to new technologies, but critical;
- verification (error awareness, content detectors, random checking of papers);
- transparency (indication of source of technology used, diversity of sources);
- upskilling (promoting knowledge, countering abuse).

The last point seems critical since raising awareness may bring many benefits. It would also be good to create so-called good practices, perhaps at the ministerial level. This would be a good reference point for creating other guidelines in individual universities. Good practices should stress student independence and critical thinking and point out areas where AI can be helpful – e.g. for brainstorming, identifying

research streams, gaps, and research methods. AI can provide a service similar to a library's scientific information department, enriching the creative process but never replacing it. Students' responsibility for their work should be addressed so they are sensitised to the possibility of intellectual property and copyright infringements.

Proper focus on AI challenges, emphasising ethics and legal issues, will increase awareness and popularise the use of AI tools - as a method to support learning and teaching.

While this chapter concentrates on teaching, scientists using generative AI in their research may encounter problems similar to those faced by didactic staff and students.

To conclude, it should be highlighted that education faces numerous challenges when using AI tools. These are, first and foremost:

- **creating appropriate regulations, guidelines, and recommendations** for using AI tools by students, lecturers, and the university's administrative environment;
- **emphasising the role of ethics and the issue of data protection** – establishing an appropriate ethical and legal framework is essential, as the widespread use of AI tools can affect human relations, emotional development and interactions in education;
- **developing technical knowledge of users regarding the AI tools and how they can be used** – teaching staff should especially be trained extensively on how to use AI in their classes and research;
- **ensuring continuous human control** so that the benefits of using AI outweigh potential limitations and risks;
- **adapting curricula to the new reality**, where AI tools are being used, to increase the competitiveness of Polish higher education in a domestic and international market.
- **working with developers, who should adapt AI tools to real educational needs** to create more attractive and functional applications for students; lecturers should work closely with developers as they are familiar with higher education and teaching specifics and should influence the creation of these apps; students should also be included in the process so that they could clarify their needs and capabilities.

The research carried out had research limitations – mainly geographical. The research concerned Polish universities, which should be taken into account when generalising the conclusions.

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Conclusions

Currently, the economic sectors and business functions in many organisations are changing due to the fast-paced technology development. Accounting, as a crucial back-office function, assists management by delivering pertinent data for proactive corporate decision-making. AI integration into accounting operations causes the accounting professions to discard old paradigms and spot exciting opportunities in the automation and digitalisation era. AI can help increase the efficacy and efficiency of many tasks, including financial planning, cost control, financial reporting, managing payables and receivables, and documenting repetitive transactions. There are several advantages related to integrating AI into accounting procedures and processes, including increased accuracy, time savings, better reporting and analysis, and increased compliance. However, drawbacks include implementation costs, specialised expertise requirements, data security threats, and problems with system dependability.

Mirjana Hladika, **Petra Halar** and **Dubravka Kopun** compared the accounting function to "the heart and a blood flow" of an organisation. This is reflected in the 'flow' of financial and other information into the accounting information system, where information is analysed and prepared in the form of annual reports and then 'flow' out to various internal and external stakeholders for their decision-making needs. The authors project that digital technology, particularly AI, will be a standard toolkit for future accountants, who will serve as strategic and dynamic value advisors to organisations' governance structures. **Mirjana Hladika**, **Petra Halar** and **Dubravka Kopun** point out that the accounting profession must adapt or draft entirely new accounting rules, policies and standards for the transformation driven by AI and human-technology interaction.

The changes affecting the accounting profession do not bypass the auditing profession either. The results of the literature review by **Piotr Bednarek** and **Paweł Miszczuk** suggest that AI applications affect both internal and external auditing, posing significant challenges but also providing some benefits. Regarding external auditing, most studies have evidenced that increased audit efficiency, effectiveness, and decision-making capabilities are the main benefits. The other advantages include increased knowledge, reduced manual work and better client-audit relationships. Regarding internal auditing, the authors remark that there is little empirical evidence about the use of AI in internal auditing. However, based on scant evidence, it can be stated that AI can help internal auditors improve the quality and efficiency of the

audit process, implementing analytical procedures to find and understand patterns and anomalies in the data sets as well as detecting subtle details that humans might miss. **Piotr Bednarek** and **Paweł Miszczuk** also highlight the role of ML and DL, which enable predictive analytics and anomaly detection, and NLP, which enhances compliance and risk assessment through text analysis, as well as RPA, which streamlines audit workflows and optimises efficiency. The authors claim that these new opportunities allow auditors to skillfully navigate complex financial landscapes and regulatory requirements, thereby enhancing the effectiveness and value of the profession.

Iztok Kolar delivers another interesting piece of evidence in this monograph. His survey results show that internal auditors in Slovenia estimate that there is a 75% probability that the profession of internal auditor will still exist in 2033. The author also examined the opinions of internal auditors on how many internal audit tasks AI will take over in 2033. The collected responses were not unequivocal, with 20% of respondents suggesting that AI will perform between 31% and 40% of internal audit tasks and 14% of respondents believing that AI will perform between 71% and 80% of internal audit tasks in 2033. Only 1% of the surveyees imply that AI will take over all the internal audit tasks in 2033. Based on these results, **Iztok Kolar** points out that AI will largely determine the future of internal audit; thus, it is high time to pay more attention to this area by internal auditors. He highlights that AI will give internal auditors more time to conduct in-depth interviews and participate in specific advisory assignments. **Iztok Kolar** remarks that the writers on the future of internal audit argue that internal auditing must change and that internal auditors should become "builders" of addressing ESG challenges in their organisations, who concentrate more on Planet, Public, Profession, Prosperity and People.

AI can also play a supportive role in reporting processes and reports' attestation. **Ana-Carolina Cojocaru (Bărbieru)**, **Svetlana Mihăilă**, **Veronica Grosu** and **Ludmila Frumusachi** claim that AI implementation in management systems can enhance and streamline the process of collecting, analysing, and reporting data related to ESG aspects. The authors have identified several advantages of implementing AI in integrated reporting through their research. These advantages include the capability to process and analyse substantial volumes of data in a timely and efficient manner, enhancing the accuracy and reliability of data, and streamlining processes through automation. On the one hand, the authors remark that the implementation of AI has the potential to enhance transparency and corporate accountability, which are crucial aspects amid growing stakeholder expectations and sustainability standards. On the other hand, they point out some data security and confidentiality challenges. They also address the issues associated with a bias risk in algorithms and the potential consequences of AI errors that necessitate stringent ethical standards and regulatory frameworks. **Assunta Di Vaio, Anum Zaffar** and **Daniel Balsalobre-Lorente** argue that advanced AI technology can help organisations report under ESG frameworks and assure and attest the sustainability reports for decarbonisation processes. For instance,

ChatReport can automate the analysis of corporate sustainability reports and retrieve relevant information about climate strategies. ChatGPT can assist organisations in revising decarbonisation strategies and improving their environmental performance. NLP may be useful for generating insights from unstructured data sources regarding sustainability reports, whereas the combination of NLP with ML has the potential to evaluate complex sustainability reporting data by proposing diverse methods to detect non-compliance with corporate social responsibility, thereby preventing greenwashing practices.

The literature review conducted by **Rasa Subačienė** and **Daiva Tamulevičienė** reveals the primary trend regarding the significance of AI or other technological advancements, their impact on business practices, and, most importantly, the necessity to modify educational curriculums to adapt to changing circumstances. The study's findings highlight AI's essential role in revolutionising business and accounting by delivering new opportunities, such as improved decision-making, predictive analytics, and operational efficiency. The authors purport that this paradigm shift means one thing for businesses and accountants – they must adopt AI-based technology to remain competitive and efficient. **Rasa Subačienė** and **Daiva Tamulevičienė** also argue for the urgent necessity to revise educational curriculums since incorporating AI into the accounting profession necessitates an education system which is responsive and adaptable to new conditions. This also requires setting the regulatory frameworks for students and academics to use generative AI. **Angelika Kaczmarczyk** analysed guidelines and recommendations for using AI in selected universities in Poland and identified two approaches in this regard – the critical and liberal ones. The critical approach points out explicitly what is allowed or not allowed and emphasises the importance of verification with content detectors and random checking. According to the author, this restrictive approach is represented by the universities in Warsaw. The liberal approach, mainly met in economic universities, addresses the openness and critical thinking of the students and relies on the autonomy of the lecturer. Most guidelines and recommendations jointly sensitise data security, privacy, and student autonomy and highlight the transparency and ethics of using AI tools. Existing regulations also draw attention to the potential threats related to the use of AI tools, including AI hallucinations, biases, and errors.

To sum up, the AI boom has already started and will last for the next few years. Since the start of the digital decade, businesses have demonstrated exponential development in their use of AI. However, to face digital ambitions successfully, business leaders will have to deal with many challenging issues, such as insufficient digital skills in the workforce, compliance and legal threats, lack of funding to digitalise businesses, and the necessity of increasing awareness of responsible AI use (Strand Partners, 2024). This book presents a critical reflection on the state and perspectives of the accountancy and auditors profession, addresses the AI technology's supportive role in accounting and auditing tasks, reporting processes

and reports' attestation, as well as stresses the necessity to modify educational curriculums in business accounting in response to changing circumstances, and set the regulatory frameworks regarding the use of generative AI by academics and students. The considerations covered in the book are timely and can be helpful for business practitioners, academics and students.

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