DOI: 10.15611/2024.58.1.02

Chapter 2

Artificial Intelligence Application in the Auditing Profession

Paweł Miszczuk
Norms Sphere Paweł Miszczuk, Poland
e-mail: pawel.miszczuk@outlook.com
ORCID: 0009-0002-9698-6435

Piotr Bednarek
Wroclaw University of Economics and Business, Poland
e-mail: piotr.bednarek@ue.wroc.pl
ORCID: 0000-0001-6394-4779

Quote as: Miszczuk, P., and Bednarek, P. (2024). Artificial Intelligence Application in the Auditing Profession. In J. Dyczkowska (Ed.), *Human versus Machine: Accounting, Auditing and Education in the Era of Artificial Intelligence* (pp. 35-48). Publishing House of Wroclaw University of Economics and Business.

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).

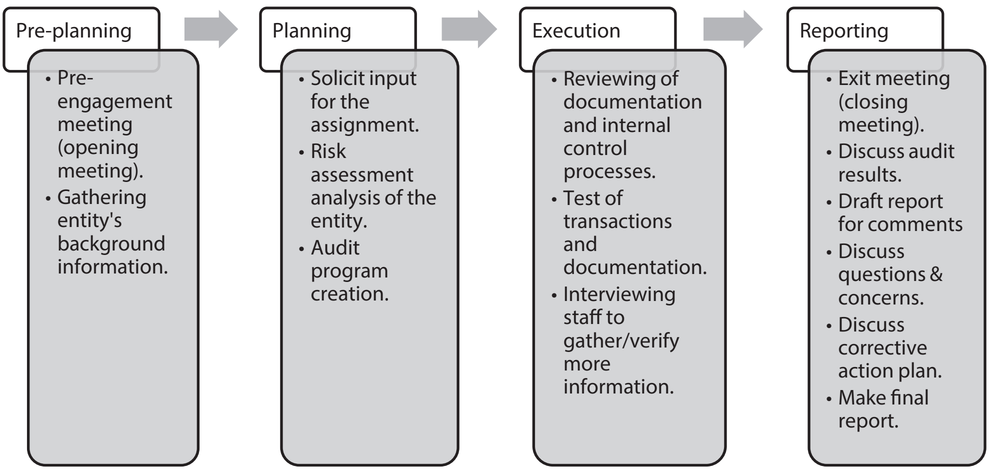

Figure 2.1. Audit process stages

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).

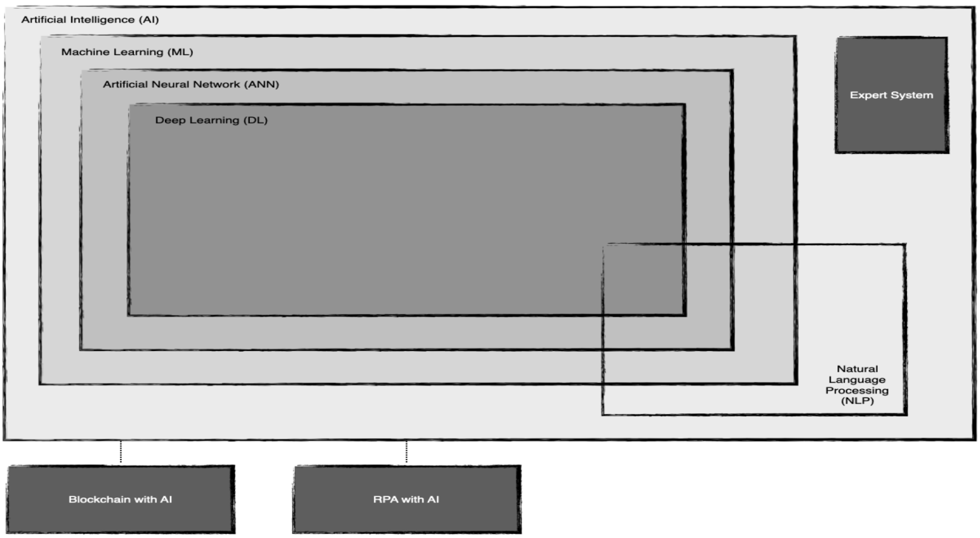

Figure 2.2. AI technologies fields

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.

References

Abdullah, H., and Almaqtari, F. (2024). The Impact of Artificial Intelligence and Industry 4.0 on Transforming Accounting and Auditing Practices. *Journal of Open Innovation: Technology, Market, and Complexity*. *10*(1), 100218. https://doi.org/10.1016/j.joitmc.2024.100218

AICPA. (2023). *Use of Technology in an Audit of Financial Statements. Practice Aid*. Retrieved April 12, 2024 from https://assets.ctfassets.net/rb9cdnjh59cm/Vf6IoQWG7diWggg2Xb7kk/b87351228d3c99ddc-4508854dc75e500/the-use-of-automated-tools-and-techniques-in-the-auditors-risk-assessment.pdf. OpenDocument.

Alaba, F., and Ghanoum, S. (2020). *Integration of Artificial Intelligence in Auditing: The Effect on the Auditing Process*. Dissertation, Kristianstad University. FE900A VT20 Master Thesis in Auditing and Control. Retrieved April 15, 2024 from https://hkr.diva-portal.org/smash/get/diva2:1446778/FULLTEXT01.pdf. OpenDocument.

Almufadda, G., and Almezeini, N. A. (2022). Artificial Intelligence Applications in the Auditing Profession: A Literature Review. *Journal of Emerging Technologies in Accounting*, *19*(2), 29-42. https://doi.org/10.2308/JETA-2020-083

Dickey, G., Blanke, S., and Seaton, L. (2019). Machine Learning in Auditing. *The CPA Journal*, *89*(6), 16-21, Retrieved April 15, 2024 from https://www.cpajournal.com/2019/06/19/machine-learning-in-auditing/. OpenDocument.

Eulerich, M., Masli, A., Pickerd, J., and Wood, D. (2022). The Impact of Audit Technology on Audit Task Outcomes: Evidence for Technology-Based Audit Techniques. *Contemporary Accounting Research*, *40*(2), 981-1012. https://doi.org/10.1111/1911-3846.1284

Fan, J., Fang, L., Wu, J., Guo, Y., and Dai, Q. (2020). From Brain Science to Artificial Intelligence. *Engineering*, *6*(3), 248-252. https://doi.org/10.1016/j.eng.2019.11.012

Fedyk, A., Fedyk, T., Hodson, J., and Khimich, N. (2022). Is Artificial Intelligence Improving the Audit Process? *Review of Accounting Studies*, *27*(3), 938-985. https://doi.org/10.1007/s11142-022-09697-x

Gao, Y., and Han, L. (2021). Implications of Artificial Intelligence on the Objectives of Auditing Financial Statements and Ways to Achieve Them. *Microprocessors and Microsystems*, 104036. https://doi.org/10.1016/j.micpro.2021.104036

Han, H., Shiwakoti, R., Jarvis, R., Mordi, C., and Botchie, D. (2023). Accounting and Auditing with Blockchain Technology and Artificial Intelligence: A Literature Review. *International Journal of Accounting Information Systems*, *48*(100598). https://doi.org/10.1016/j.accinf.2022.100598

Hasan, A. R. (2022). Artificial Intelligence (AI) in Accounting & Auditing: a Literature Review. *Open Journal of Business and Management*, *10*(01), 440-465. https://doi.org/10.4236/ojbm.2022.101026

Hashid, A., and Almaqtari, F. (2024). The Impact of Artificial Intelligence and Industry 4.0 on Transforming Accounting and Auditing Practices. *Journal of Open Innovation: Technology, Market, and Complexit*y, *10*(1), 100218. https://doi.org/10.1016/j.joitmc.2024.100218

Holmes, A., and Douglass, A. (2022). Artificial Intelligence: Reshaping the Accounting Profession and the Disruption to Accounting Education. *Journal of Emerging Technologies in Accounting*, *19*(1), 53-68. https://doi.org/10.2308/JETA-2020-054

Huang, F., and Wang, Y. (2023). Introducing Machine Learning in Auditing Courses. *Journal of Emerging Technologies in Accounting*, *20*(1), 195-211. https://doi.org/10.2308/JETA-2022-017

Huson, Y. A., Sierra-García, L., and Garcia-Benau, M. A. (2023). A Bibliometric Review of Information Technology, Artificial Intelligence, and Blockchain on Auditing. *Total Quality Management & Business Excellence*, *35*(1-2), 91-113. https://doi.org/10.1080/14783363.2023.2256260

IBM. (n.d.) *What is Artificial Intelligence (AI)?* Retrieved April 12, 2024 from https://www.ibm.com/topics/artificial-intelligence. OpenDocument.

Institute of Internal Auditors. (2024). *Definition of Internal Auditing*. Retrieved April 12, 2024 from https://www.theiia.org/en/standards/what-are-the-standards/definition-of-internal-audit/. OpenDocument.

Issa, H., Sun, T., and Vasarhelyi, M. (2016). Research Ideas for Artificial Intelligence in Auditing: The Formalization of Audit and Workforce Supplementation. *Journal of Emerging Technologies in Accounting*, *13*(2), 1-20. https://doi.org/10.2308/jeta-10511

Kokina, J., and Davenport, T. H. (2017). The Emergence of Artificial Intelligence: How Automation is Changing Auditing. *Journal of Emerging Technologies in Accounting, 14*(1), 115-122. https://doi.org/10.2308/jeta-51730

Liu, W., Yen, M., and Wu, T. (2022). Report Users' Perceived Sentiments of Key Audit Matters and Firm Performance: Evidence From a Deep Learning-Based Natural Language Processing Approach. *Journal of Information Systems*, *36*(3), 191-209. https://doi.org/10.2308/ISYS-2020-061

Minkkinen, M., Laine, J., and Mäntymäki, M. (2022). Continuous Auditing of Artificial Intelligence: A Conceptualisation and Assessment of Tools and Frameworks. *Digital Society, 1*(3), 21. https://doi.org/10.1007/s44206-022-00022-2

Moffitt, K. C., Rozario, A. M., and Vasarhelyi, M. A. (2018). Robotic Process Automation for Auditing. *Journal of Emerging Technologies in Accounting*, *15*(1), 1-10. https://doi.org/10.2308/jeta-10589

Mökander, J., Schuett, J., Kirk, H. R., and Floridi, L. (2023). Auditing Large Language Models: A Three-Layered Approach. *AI Ethics*. https://doi.org/10.1007/s43681-023-00289-2

Munoko, I., Brown-Liburd, H. L., and Vasarhelyi, M. (2020). The Ethical Implications of Using Artificial Intelligence in Auditing. *Journal of Business Ethics*, *167*(2), 209-234. https://doi.org/10.1007/s10551-019-04407-1

Ng, C. (2023). Teaching Advanced Data Analytics, Robotic Process Automation, and Artificial Intelligence in a Graduate Accounting Program. *Journal of Emerging Technologies in Accounting*, *20*(1), 223-243. https://doi.org/10.2308/JETA-2022-025

Patil, R., Kulkarni, S., and Gaikwad, V. (2023). Artificial Intelligence in Pharmaceutical Regulatory Affairs. *Drug Discovery Today*, *28*(9), 103700. https://doi.org/10.1016/j.drudis.2023.103700

Saranya, A., and Subhashini, R. (2023). A Systematic Review of Explainable Artificial Intelligence Models and Applications: Recent Developments and Future Trends. *Decision Analytics Journal*, *7*(5), 100230. https://doi.org/10.1016/j.dajour.2023.100230

Zemánková, A. (2019). Artificial Intelligence and Blockchain in Audit and Accounting: Literature Review. *WSEAS Transactions on Business and Economics*, *16*, 568-581.

Zhang, C., Thomas, C., and Vasarhelyi, M. (2022). Attended Process Automation in Audit: A Framework and a Demonstration. *Journal of Information Systems*, *36*(2), 101-124. https://doi.org/10.2308/ISYS-2020-073