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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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