WORKING PAPER

Artificial Intelligence in Auditing

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KEY TAKE-AWAYS

Four insights from the literature on the effects of AI on audit practice
• AI is improving audit quality and efficiency

The literature consistently shows that, when properly implemented, AI strengthens audit effectiveness. AI helps auditors to identify fraud risks, detect misstatements, analyze entire populations of transactions rather than samples, and reduce human error. What is more, it automates repetitive and time-consuming tasks, allowing audits to be completed more efficiently.

Key message: Overall, AI is enhancing both the effectiveness and efficiency of audit engagements, supporting the profession's ability to provide timely and reliable assurance.
• AI changes auditors' work experience in both positive and negative ways…

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Artificial Intelligence in Auditing: A Review of its Effects and a Demands–Resources Framework for Future Research

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A Review of its Effects and
a Demands–Resources Framework for Future Research

Abstract

Artificial Intelligence (AI) is steadily transforming audit practice, bringing both benefits and challenges. Building on existing theory and on the tension between AI's benefits and challenges, we develop the AI Demands-Resources Framework for Auditing (AD-RFA). We use this framework to map the findings from extant literature investigating the effects of AI on audit practice. The effects are structured along two dimensions, i.e., the type of audit practice factor they represent (demand or resource) and the level of outcomes resultant from these effects (individual-level or firm-level). Finally, we suggest avenues for future research.

Keywords:

Artificial Intelligence, audit, auditor, demands, resources, systematic literature review

Artificial Intelligence in Auditing: A Review of its Effects and a Demands–Resources Framework for Future Research

1 Introduction

Artificial Intelligence (AI) is steadily transforming modern businesses, firms, and society (Broekhuizen et al., 2023). The rapid pace of AI's development in the last few years has changed how business processes operate (Enholm et al., 2022), including those in audit practice. AI refers to "a broad class of technologies that allow a computer to perform tasks that normally require human cognition" (Tambe et al., 2019, p. 16), such as "perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity" (Rai et al., 2019, p. 3). Over the last few years, the investments in the development of AI capabilities for audit practice, which refers to the set of procedures and judgments used to provide assurance (Power, 2003), have been intensified (Commerford et al., 2022; Fedyk et al., 2022). For example, in 2025, EY announced another phase of its US$1 billion investment plan aimed at integrating AI into its audit engagements (EY, 2025). In the same year, Deloitte announced that it had begun introducing AI within its audit and assurance services, including generative AI, stating that these tools are necessary for addressing the complexity of the modern audit environment (Deloitte, 2025).

Given the significant speed of AI adoption in audit practice, research calls for an assessment of the challenges and benefits that AI introduces (Kokina et al., 2025). Existing research has started to discern specific effects of AI, including its impact on audit accuracy (Fedyk et al., 2022; Gu et al., 2024; Osei-Assibey Bonsu et al., 2023), audit speed (Christ et al., 2021; Lin et al., 2003; Rahman et al., 2024), audit market structure (Kend & Nguyen, 2020; Law & Shen, 2025), or individual auditors' experience (Lajoie & Gendron, 2025; Samiolo et al., 2024). While this literature highlights both the benefits and challenges introduced by AI, its fragmented nature makes it difficult to develop a comprehensive understanding of AI's overall impact on audit practice – an understanding that is crucial for navigating the safe and sustainable implementation of AI. This study develops such a comprehensive overview of AI effects on audit practice and points researchers at future directions that may prove fruitful in furthering our understanding of the benefits and challenges associated with AI in audit practice.

For this purpose, we use the Job Demands-Resources (JD-R) model (Bakker et al., 2003, Bakker & Demerouti, 2007) as a theoretical foundation and adapt it to the context of AI in auditing. The adapted version is labeled the AI Demands-Resources Framework for Auditing (AD-RFA) and suggests that AI effects can manifest as demands or resources for audit practice. The AD-RFA positions AI effects as demands for audit practice when they create additional work pressure or workload for the individual auditors, amplifying their job strain, or when they disturb the audit effectiveness; hereby, audit effectiveness is defined as the extent to which an audit firm fulfills its objectives without incapacitating its means (Georgopoulos, 1957). In contrast, AI effects are positioned as audit practice resources when they eliminate the job strain individual auditors face, leading to enhanced job satisfaction, or when they facilitate audit effectiveness (Lesener et al., 2019). In addition, the AD-RFA distinguishes between individual- and firm-level outcomes (Podsakoff et al., 2009) resulting from AI. Individual-level outcomes refer to consequences that directly affect auditors, meaning changes in work pressure, workload, and consequently, in job strain or job satisfaction. Firm-level outcomes capture the consequences of AI effects on audit firms, particularly through changes in audit effectiveness.

We conducted a systematic literature review of prior research on AI effects on audit practice, which we subsequently structured using the AD-RFA, which offers a lens for synthesizing existing insights on AI effects on audit practice and for assessing their implications for auditors and audit firms. Throughout the review, we identified seven key effects of AI on audit practice along the AD-RFA dimensions: *cognitive load from skills shift*, and *fear of professional obsolescence* experienced by individual auditors, *auditors' deskilling*, as well as *auditors' over- and under-reliance* on AI, *decreased workload and enhanced job meaningfulness*, *increased efficiency*, and *increased accuracy*. Additionally, we uncovered four future research directions that emerge from our work. First, more attention is needed on AI outcomes on the individual level, particularly, how AI and its effects influence auditors' psychological and professional well-being, including job satisfaction, engagement, and burnout, across different levels of auditors' exposure to AI. Second, there is a need for more research on AI-driven auditors' deskilling, examining whether measurable differences exist in auditors' skills, knowledge, judgment, and skepticism based on their exposure to AI, what can prevent such deskilling, and how it affects audit practice at the firm level, for example, in terms of audit quality. Third, in line with auditors' over- and under-reliance behaviour, research should clarify the appropriate level of reliance on AI, especially given its "black box" nature (Dourish, 2016; Lebovitz et al., 2022; Rai, 2020), by investigating how auditors' reliance should vary across tasks, how auditors can effectively verify and challenge AI-generated outputs, and what the implications of different verification methods are for firm-level effectiveness. Finally, future studies should adopt a more integrative perspective by examining how the various effects of AI interact, how they translate from individual- to firm-level outcomes, and how these dynamics evolve as AI technologies continue to develop.

The remainder of this paper proceeds as follows: Section 2 presents the AD-RFA. Section 3 presents the research method and sample description. In Section 4, we review literature and describe seven identified effects of AI on audit practice that represent demands or resources for individual auditors or audit firms, and provide future research directions. Section 5 summarizes the main insights and concludes.

2 Theoretical Background and Conceptual Framework

Since the burgeoning of AI, research has shown increasing interest in AI's impact on audit practice. Various papers suggest that AI brings benefits to audit practice. AI decreases the incidence of audit restatements (Fedyk et al., 2022; Rahman et al., 2024), lowers the error rate within various audit procedures (Christ et al., 2021), reduces fraud possibilities (Lin et al., 2003; Osei-Assibey Bonsu et al., 2023), eliminates human errors, and facilitates better judgment among auditors, allowing higher audit accuracy (Law & Shen, 2025; Rahman et al., 2024).

At the same time, AI in auditing is associated with a wide range of risks. Research shows that AI can compromise audit clients' privacy and confidentiality, create data security risks (Eisikovits et al., 2025), and produce biased and inaccurate results (Fotoh et al., 2025) that have a range of negative consequences, from incorrect audit conclusions to unfair decisions and discrimination against clients

(Eisikovits et al., 2025). In addition, AI-driven automation raises concerns about the individual auditors' displacement (Siddiqui & Raheman, 2025), isolation (Munoko et al., 2020), and the diminishing of their professional judgment (Samiolo et al., 2024), while the broader literature on AI in the workplace highlights the risk of AI-driven employees' identity threats (Mirbabaie et al., 2022) and threats to employees' well-being (Złotowski et al., 2017).

Such ambivalent effects of AI, which simultaneously bring both challenges and benefits to audit practice, call for a structured review of their implications for practice (Kokina et al., 2025). Based on this call, we develop the AI Demands-Resources Framework for Auditing (AD-RFA) to structure existing knowledge of AI effects on audit practice. The framework builds on the Job Demands-Resources model (Bakker & Demerouti, 2007; Demerouti et al., 2001), which is specifically suitable to capture benefits and challenges arising from various workplace phenomena. Accordingly, Subsection 2.1 presents the JD-R model as the theoretical foundation, while Subsection 2.2 introduces the AD-RFA as its adaptation to synthesise AI effects on audit practice.

2.1 The Job Demands–Resources Model as a Theoretical Foundation

The Job Demands-Resources model posits that every occupation involves specific physical, psychological, social, or organizational factors that characterize its work conditions (Demerouti et al., 2001). These factors can be classified into two general categories, i.e., job demands and job resources. Job demands refer to the factors that require sustained physical and psychological (cognitive and emotional) efforts or skills from the employees involved, and are associated with material and or immaterial costs. Meanwhile, job resources refer to the factors that reduce employees' job strain and facilitate the attainment of organizational objectives (Bakker & Demerouti, 2007). The JD-R model further explains the psychological processes behind the development of employees' job strain and job satisfaction. Specifically, it shows that as individuals in the organization increasingly face job demands, it causes their mental and physical exhaustion, depletion of energy, and ultimately contributes to their job strain. In contrast, job resources foster individuals' job motivation, mitigate their job strain, and enhance their job satisfaction (Bakker et al., 2003; Bakker & Demerouti, 2007, 2017).

2.2 The AI Demands-Resources Framework for Auditing (AD-RFA)

Building on the JD-R model, the AD-RFA categorizes the effects of AI on audit practice in terms of the *type of audit practice factor* they represent, positioning AI effects as demands or as resources to audit practice. In line with the JD-R, the AD-RFA positions AI effects as audit practice demands when they intensify auditors' job strain, or when they disturb the audit effectiveness. AI effects are positioned as audit practice resources when they enhance auditors' job satisfaction or when they facilitate audit effectiveness. Additionally, the AD-RFA distinguishes between two *levels of outcomes* resulting from the effects of AI on audit practice. Specifically, it differentiates between the outcomes for the individual auditors and for the audit firms. Individual-level outcomes capture consequences of AI effects that can be assessed for each individual auditor, reflecting changes in their experiences and behaviors. In contrast, firm-level outcomes represent consequences measured at the office or firm level, including changes in factors like firm performance or reputation (Podsakoff et al., 2009).

Applied to audit practice, AI-related demands exhaust employees' mental and physical resources and are thus associated with increased job strain among auditors (individual-level outcome) (Bakker et al., 2003; Bakker & Demerouti, 2007, 2017; Hakanen et al., 2006; Lesener et al., 2019). Moreover, AI-related demands also affect audit firm performance and, consequently, general audit effectiveness (firm-level outcomes). Audit practice resources are associated with increased job satisfaction in auditors (individual-level outcome) and improved audit firm effectiveness (firm-level outcome) (Bakker & Demerouti, 2017; Lesener et al., 2019). The developed framework is depicted in Figure 1.

		Level of outcome	
		Individual-level	**Firm-level**
Type of audit practice factor	**Demand**	AI-driven auditors' job strain	AI-driven decline in audit effectiveness
	Resource	AI-driven auditors' job satisfaction	AI-driven improvement in audit effectiveness

Fig. 1. *AI Demands-Resources Framework for Auditing (AD-RFA). Notes: The framework positions AI effects as either demands or resources for audit practice, and links them to individual-level outcomes (auditors' job strain and job satisfaction) and firm-level outcomes (audit effectiveness).*

3 Methodology and sample description

Using a systematic literature review, we identify and deductively categorize auditing literature based on the AD-RFA dimensions. The use of a systematic search process and presentation of existing research findings reduces subjectivity, thus providing the academic and practice audience with a reasonably objective representation of the current state of the research on the effects of AI on audit practice (Baumeister & Leary, 1997; Siddaway et al., 2019). We identified and screened the relevant research articles following the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) Flow Diagram (Moher et al., 2009) (see Figure 2), described in more detail in the sub-sections that follow. Specifically, Subsection 3.1 describes how relevant literature was systematically identified using predefined search criteria and sources, while Subsection 3.2 explains how these studies were screened and filtered to obtain the final sample.

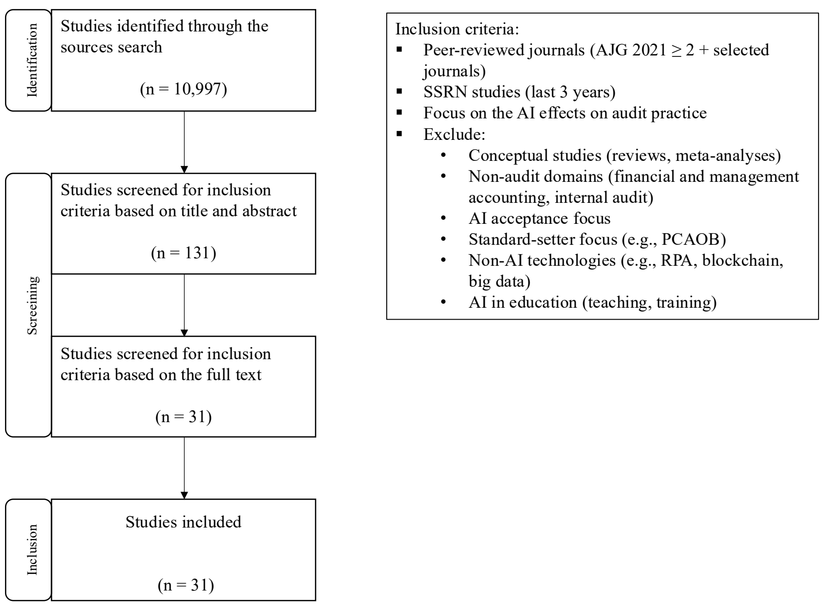

Fig. 2. *Sample selection process and inclusion criteria*

3.1 Identification of the relevant literature

We used Google Scholar as the main search database and used its advanced search function to review only studies published in 63 leading journals in the broader accounting and auditing discipline. Specifically, we consider (1) journals that are rated 2 or higher and classified as accounting journals based on the Academic Journal Guide (AJG) of the Chartered Association of Business Schools (2021)[1], (2) the Journal of Information Systems, and the Journal of Forensic Accounting Research, [2] and (3) the journal Management Science[3].

We used the search string ("audit*") AND ("AI" OR "Artificial Intelligence"), applied to anywhere in the text of the papers, and included all studies published up to March 1st, 2026, with no restriction on the earliest publication date.

Additionally, considering the growing research attention on the effects of AI on audit practice and the rapid progress in AI (Eisikovits et al., 2025), to ensure that our review reflects the most recent developments in the literature, we included relevant studies published on the Social Science Research Network (SSRN)[4] during the last three years[5]. Using the search function provided on SSRN, we applied

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[1] This includes: Accounting Review; Accounting, Organizations and Society; Journal of Accounting and Economics; Journal of Accounting Research; Contemporary Accounting Research; Review of Accounting Studies; Abacus; Accounting and Business Research; Accounting Forum; Accounting Horizons; Accounting, Auditing and Accountability Journal; Auditing; Behavioral Research in Accounting; British Accounting Review; British Tax Review; Critical Perspectives on Accounting; European Accounting Review; Financial Accountability and Management; Foundations and Trends in Accounting; International Journal of Accounting; Journal of Accounting and Public Policy; Journal of Accounting Literature; Journal of Accounting, Auditing and Finance; Journal of Business Finance and Accounting; Journal of International Accounting, Auditing and Taxation; Journal of the American Taxation Association; Management Accounting Research; Accounting and Finance; Accounting and the Public Interest; Accounting in Europe; Accounting Research Journal; Accounting, Economics and Law: A Convivium; Advances in Accounting; Advances in Accounting Behavioral Research; Advances in Management Accounting; Advances in Taxation; Asia-Pacific Journal of Accounting and Economics; Asian Review of Accounting; Australian Accounting Review; China Journal of Accounting Research; Current Issues in Auditing; International Journal of Accounting and Information Management; International Journal of Accounting Information Systems; International Journal of Accounting, Auditing and Performance Evaluation; International Journal of Auditing; International Journal of Disclosure and Governance; International Journal of Managerial and Financial Accounting; Journal of Accounting and Organizational Change; Journal of Accounting in Emerging Economies; Journal of Applied Accounting Research; Journal of Contemporary Accounting and Economics; Journal of International Accounting Research; Journal of International Financial Management and Accounting; Journal of Management Accounting Research; Journal of Management Control; Journal of Public Budgeting, Accounting and Financial Management; Journal of Tax Administration; Managerial Auditing Journal; Qualitative Research in Accounting and Management; Sustainability Accounting, Management and Policy Journal.

[2] The *Journal of Information Systems*, and the *Journal of Forensic Accounting Research* are journals published by the American Accounting Association, but are not classified as primarily accounting by the AJG. We included them due to their relevance to the research topic.

[3] The journal *Management Science* is not classified as primarily accounting by the AJG, but is a top journal with a dedicated accounting track.

[4] Social Science Research Network (SSRN) is a platform for sharing academic research papers (especially in the social sciences), often before formal publication.

[5] The timeframe assumes that the publication process in the selected journals can take about three years. During the preparation of this literature review, we observed that some of the studies initially identified as gray literature through SSRN were subsequently published in one of the selected journals (e.g., Fabian & Ratzinger-Sakel, 2026; Peecher et al., 2026), which further supports the relevance of including gray literature in our review.

the following search string for the title, abstract, and keyword of the study[6]: (audit*) AND (AI OR Artificial Intelligence). We included studies uploaded within the three years prior to 1 March 2026.

Overall, the described identification procedure led to 10,997 studies published in one of the selected journals or available through SSRN.

3.2 Screening of the identified literature

After identifying the potentially relevant studies, we screened their titles and abstracts and excluded studies based on the criteria related to the research method and the topic of the studies. First, we included only empirical quantitative and qualitative studies that consider the effects of AI on audit practice, excluding conceptual works such as meta-analyses and literature reviews.

Second, we included studies that use the term "AI" as a central term of their research, as well as studies that examine the impact of specific technologies categorized as AI-based, such as machine learning (ML) models, AI-based visual recognition technologies (VRT), large language models (LLMs), and fuzzy neural networks (FNNs). We also include studies that analyze the effects of technologies more broadly when they explicitly state that AI-based technologies are part of the technologies considered. We excluded studies that focused on technologies other than AI, such as data analytics, big data, robotic process automation (RPA), and blockchains. Such technologies appeared in the search results as they have certain operational similarities to AI but do not inherently involve cognitive or learning capabilities that define AI technologies (Rai & Sarker, 2019). We excluded studies focused on financial accounting and reporting, management accounting and control, or internal auditing, as they occasionally appear in the search but do not directly address AI effects on audit practice. We excluded studies that examined factors influencing the acceptance of AI by auditors or other audit stakeholders, as they are not directly relevant to understanding the effects of AI on audit practice, or studies focused on standard setters such as the PCAOB and their position towards AI. Finally, we excluded studies focused on AI impact on the formal university or institutional education for auditors, as well as those examining the impact of AI on

[6] Full-text searches were conducted within selected journals to increase the likelihood of identifying all relevant studies, given that relevant constructs may not be fully captured in titles, abstracts, or keywords. In contrast, searches on SSRN were restricted to titles, abstracts, and keywords to improve precision and mitigate the high volume of non-peer-reviewed working papers.

teaching practices within these educational settings. Based on the screening of the title and abstract, we identified 131 studies that meet the specified criteria.

In the next screening step, we conducted a full-text screening of these identified studies. To identify studies that meet all the inclusion criteria, we developed a structured data extraction sheet to systematically capture information from all 131 studies that were identified through the title and abstract screening. The sheet records key bibliographic details (e.g., journal name, year, article reference, and link), type of AI (e.g., general AI, LLM, or ML) discussed, data collection method, and inclusion decisions and reasons for exclusion. Subsequently, this led to the further exclusion of 100 studies. The primary reasons for exclusion included conceptual nature, lack of focus on external audit practice (e.g., emphasis on general accounting or internal audit), and a primary focus on other technologies such as data analytics, which were not evident from the title and abstract screening alone. The final sample was 31 studies, which are included in the final literature review. Appendix 1 lists the 31 included studies.

4 Findings

A large portion of the reviewed literature focuses on AI effects on the audit process and its operational measures, including AI effects on audit quality (Fedyk et al., 2022; Gu et al., 2024; Lin et al., 2003; Osei-Assibey Bonsu et al., 2023), audit efficiency (Christ et al., 2021; Li et al., 2024; Wang et al., 2025; Wu et al., 2025), and audit costs (Fedyk et al., 2022; Law & Shen, 2025). A smaller group of reviewed studies explores the effects of AI on the general structure of the audit industry, describing how AI affects the audit labor market, including its size and requirements (Fedyk et al., 2022; Gu et al., 2024; Law & Shen, 2025; Vitali & Giuliani, 2024), the gap between the Big 4 and smaller audit firms (Kend & Nguyen, 2020; Vitali & Giuliani, 2024), audit firms' reputation (Libby & Witz, 2024) and relationships with their clients (Koreff et al., 2023). Lastly, the smallest part of the reviewed literature discusses AI effects on the individual auditors, exploring the sense of uncertainty AI causes among them (Siddiqui & Raheman, 2025), its impact on auditors' judgment and skepticism (Samiolo et al., 2024), and on their work experience (Vitali et al., 2024).

By synthesizing findings reported in the reviewed literature and grouping similar results, we identify seven key AI effects that map onto the dimensions of the AD-RFA—type of audit practice factor (demand vs. resource) and level of outcome (individual vs. firm). On the demands–individual level, AI increases auditors' job strain through (1) *cognitive load from skill shifts*, as auditors must develop new competencies that require significant mental resources (Sweller, 1988, 1994), and (2) *fear of professional obsolescence*, which creates emotional exhaustion and the sense of job insecurity (Llosa et al., 2018). On the demands–firm level, AI leads to a decline in audit effectiveness, which refers to the extent to which audit firms can fulfill their objectives, via (3) *auditors' deskilling*, where reduced exposure to routine tasks weakens their judgment development (Samiolo et al., 2024), and (4) *auditors' over- and under-reliance on AI*, both of which have the potential to distort evidence evaluation and harm audit quality (Commerford et al., 2022; Kokina & Davenport, 2017). In contrast, on the resources–individual level, AI enhances auditors' job satisfaction through (5) *decreased workload and enhanced job meaningfulness*, as it reduces repetitive tasks auditors are involved in, allowing them to focus on more value-adding activities (Kend & Nguyen, 2020; Vitali & Giuliani, 2024). Finally, on the resources–firm level, AI improves audit effectiveness through (6) *increased efficiency* by speeding up the audit process and (7) *increased accuracy* by enhancing the precision of audit conclusions. Together, these effects show that AI simultaneously creates challenges and benefits across both individuals and firms, reinforcing the framework's core idea that AI acts as both a demand and a resource to audit practice. Figure 3 summarizes the identified effects.

		Level of outcome	
		Individual-level	**Firm-level**
Type of audit practice factor	**Demand**	AI-driven auditors' strain 1. *Cognitive load from skills shift* 2. *Fear of professional obsolescence*	AI-driven decline in audit effectiveness 3. *Auditors' deskilling* 4. *Auditors' over- and under-reliance*
	Resource	AI-driven auditors' satisfaction 5. *Decreased workload and enhanced job meaningfulness*	AI-driven improvement in audit effectiveness 6. *Increased efficiency* 7. *Increased accuracy*

Fig. 3. *AI Demands-Resources Framework for Auditing (AD-RFA). Notes: The framework summarizes the key effects AI exerts on audit practice and positions them onto the dimensions of the AD-RFA—type of audit practice factor (demand vs. resource) and level of outcome (individual vs. firm).*

4.1 AI-driven auditors' strain

4.1.1 Cognitive load from skills shift

The first identified effect of AI on audit practice is the *cognitive load from the skills shift.* Cognitive load is defined as the effort that performing a particular task requires from an individual's mental system (Paas et al., 2003). AI changes how audit practice operates, which shifts the types of skills auditors have to possess at their jobs, requiring them to acquire new skills. The process of new skills acquisition represents a task that places cognitive load on auditors, consuming their mental resources and increasing their mental strain (Sweller 1988, 1994). Therefore, from the perspective of the AD-RFA, this effect of AI is a demand for audit practice that generates individual-level outcomes. The literature in this area uncovers a skill shift both in terms of technical skills and in terms of soft skills. From a technical perspective, Vitali & Giuliani (2024) identified to the need to enhance technical skills among auditors. Through interviews with practicing auditors, the study highlights the general belief among practitioners that with the rise of AI in audit practice, auditors will have to possess IT and computer science knowledge – something that most of the auditors do not currently hold (Vitali & Giuliani, 2024). While the demand for an enhancement of auditors' technical skills may be rather unsurprising, interestingly, Law & Shen (2025), show, with their archival study focused on the USA labor market, that AI use by the audit firm is associated with an increased demand for soft skills in auditors' positions, including cognitive abilities, efficiency, and customer service. The increased demand for the auditors' soft skills is explained by auditors' increased involvement in analytical and interpretative work, as well as by the AI-driven expansion in cross-team communication, for example, between audit teams and AI developers (Law & Shen, 2025).

4.1.2 Fear of professional obsolescence

The second effect of AI on audit practice we identified from the review is the *fear of professional obsolescence* AI causes among individual auditors and other involved stakeholders. Professional obsolescence refers to the audit profession becoming useless due to the external changes, specifically AI development (Siddiqui & Raheman, 2025). The fear of AI-caused professional obsolescence is a phenomenon that is widely observed among various professions (Złotowski et al., 2017). Prior research shows that fear of professional obsolescence is associated with an increased risk of depression, anxiety, and emotional exhaustion (Llosa et al., 2018), contributing to higher levels of job strain. Therefore, from the perspective of the AD-RFA, this effect of AI is a demand for audit practice with individual-level outcomes.

The studies in this area either focus on the expectations associated with professional obsolescence or on actual audit labour market dynamics hinting at obsolescence (or at the opposite). Siddiqui & Raheman (2025), as well as Tiberius & Hirth (2019) belong to the studies that focus on expectations regarding a potential professional obsolescence in auditing. Through a qualitative thematic analysis of the comments received by the IAASB on their consultation paper titled "*Exploring the Growing Use of Technology in the Audit, With a Focus on Data Analytics*", Siddiqui & Raheman (2025) show that audit stakeholders perceive AI as impactful for the relevance of the audit profession, emphasizing their concerns that AI-driven automation can make the audit profession obsolete in the near future. They further show that the audit stakeholders highlight the need for regulatory bodies to adapt to the AI-driven changes in the audit environment, ensuring the relevance of the audit profession (Siddiqui & Raheman, 2025). In their Delphi study, Tiberius & Hirth (2019) come to a different conclusion; they find that audit users like shareholders, lenders, financial analysts, and other stakeholders do not expect AI to render the profession obsolete in the near future. Specifically, they show that audit users do not expect auditors' judgment to become obsolete or for automated procedures to surpass manual ones in trustworthiness. However, their conclusion may now be somewhat outdated, given the fact that their projections were limited to a five- to ten-year horizon (Tiberius & Hirth, 2019)—potentially explaining the difference in findings to Siddiqui & Raheman (2025).

When it comes to the actual dynamics on the market, it remains unclear whether the fear that auditors will become professionally obsolete is actually materializing, as existing evidence is contradictory. For example, Fedyk et al. (2022) show that an audit firm's investments in AI capabilities are associated with a decrease in the number of audit employees employed by that firm a few years after the investments, with the association being especially strong for junior auditors. At the same time, a study by Law & Shen (2025), which, similarly to Fedyk et al. (2022), is based on the USA labor market data, demonstrates the contrary results, suggesting that the use of AI by the audit firms is actually associated with a larger number of audit jobs available.

Regardless of whether these fears reflect actual labor market developments or are primarily perceptual, the experience of job insecurity, caused by the fear of professional obsolescence, has well-documented negative consequences for individuals' mental health. As mentioned earlier, perceived job insecurity is associated with an increased risk of depression, anxiety, and emotional exhaustion (Llosa et al., 2018), contributing to higher levels of job strain (Bakker & Demerouti, 2007). Consequently, this effect of AI can be understood as a job demand within audit practice, with psychological outcomes for individual auditors, and is placed on the demands–individual level quarter of the AD-RFA.

4.2 AI-driven decline in audit firms' effectiveness

4.2.1 Auditors' deskilling

The third identified effect that AI induces on audit practice is the *auditors' deskilling*. AI-driven professionals' deskilling is a phenomenon observed among various industries (Fredman, 2025). It is defined as the erosion of competencies through decreased practice, cognitive offloading, and a shift from primary task execution to monitoring of AI (Natali et al., 2025), which can lead to professionals' cognitive dependence on automated recommendations and weakened independent judgment and adaptability (Heudel et al., 2026). In the audit industry specifically, by automating and overtaking many labor-intensive audit tasks, AI contributes to auditors' deskilling (Kend & Nguyen, 2020; Samiolo et al., 2024), compromising auditors' judgments and disturbing clients' trust. Therefore, from the perspective of the AD-RFA, this effect of AI is a demand for audit practice with firm-level outcomes.

This area of research encompasses findings from within and outside audit firms, thus providing a broad view on auditors' deskilling. This issue of deskilling and its negative impact on audit quality is explored by Koreff et al. (2023) from the perspective of audited firms. Based on interviews with auditees from the healthcare sector, Koreff et al. (2023) show that auditees sometimes perceive auditors who rely on AI as lacking the necessary expertise and professional judgment to interpret audit evidence, substituting the lack of judgment with AI use. Their findings indicate that auditors' deskilling poses risks not only to audit quality but, consequently, also to audit firms' reputation and client relationships. A study by Fuchs et al. (2025a), drawing on a series of interviews with audit practice stakeholders, shows that due to the efficiency benefits that AI brings to audit practice, combined with cost-saving expectations on the client side, audit firms face increasing pressure to rethink and redesign their processes and labor structures. This transformation changes how audit work is distributed between human professionals and AI systems (Fuchs et al., 2025a). AI increasingly handles data collection, processing, and basic analytical work, while auditors have fewer opportunities to engage in experiential learning, which is essential for building professional judgment and expertise. Their findings further suggest that AI poses the risk of diminishing the scope of knowledge-intensive professional work that may lead to the auditors' deskilling and hindered professional judgment in the longer-term (Fuchs et al., 2025a).

Samiolo et al. (2024) furthers the discussion on the potential for deskilling by researching it from the perspective of auditors themselves. Samiolo et al. (2024) argue that AI-driven automation and standardization disturb auditors' learning process, especially for junior professionals. Specifically, their findings show that auditors who start their career at the age of AI do not perform highly structured, routine, and standardized audit tasks, such as transaction analysis, as those tasks are being perpetually automated. Therefore, junior auditors might be at risk of not developing a holistic perspective on the audit process, which compromises their judgment and ability to interpret AI output critically (Samiolo et al., 2024). The authors conclude that AI-driven automation poses deskilling risks, particularly for junior auditors, whose reduced involvement in routine tasks may limit opportunities to develop critical judgment during the audit process. Moreover, they argue that as routine tasks become automated, auditors in general may become less prepared for higher-level work requiring complex judgment, suggesting that deskilling risks may extend beyond junior auditors to professionals across different levels of experience (Samiolo et al., 2024). Auditors' deskilling and hindered professional judgment impose risks to the audit quality, especially considering AI's tendency to produce biased or inaccurate outputs (Eisikovits et al., 2025; Fotoh et al., 2025; Föhr et al., 2023).

Whether AI threatens skills and judgment development for auditors in general or only for junior auditors in particular, by hindering skill development, AI creates risks that auditors will not be able to critically judge in the course of an audit (Fuchs et al., 2025a; Samiolo et al., 2024), threatening audit quality. Such an apprehended threat to the quality is further affecting audit firms' relationships with their clients, disturbing auditees' trust (Koreff et al., 2023) – something that is greatly valued by the audit firms (Klein & Leffler, 1981), ultimately placing this effect on the demand–firm level quarter of the AD-RFA.

4.2.2 Auditors' over- and under-reliance

The fourth identified effect that AI brings to audit practice is the form of compromised professional judgment, specifically, *auditors' over- and under-reliance* on AI-generated outputs, which refers to auditors' deficient judgment in which they either place excessive trust in, or unjustifiably discount, AI-generated outputs. This leads to an imbalanced evaluation of audit evidence and compromises audit quality. This effect aligns with the phenomenon of auditors' deskilling and potentially could be seen as a consequence or antecedent of deskilling, although future research should further explore the connection between these effects. Auditors' over- and under-reliance on AI-generated outputs can lead to the acceptance of wrong audit evidence, compromising audit quality (Commerford et al., 2022; Kokina et al., 2025). Therefore, from the perspective of the AD-RFA, this effect of AI is also conceptualized as a job demand at the firm level, with implications for overall audit effectiveness. This section reviews the literature on auditors' over- and under-reliance on AI, factors that intensify or mitigate it, as well as its negative consequences for audit practice. The reviewed literature primarily distinguishes between under-reliance (algorithm aversion) and over-reliance, and examines the factors that influence these behaviors as well as their consequences for audit practice.

Commerford et al. (2022, 2024) show evidence that individual auditors exhibit algorithm aversion, often discounting AI output when receiving contradicting information from a human colleague. Additionally, they showed that this tendency is amplified when the information from human colleagues is perceived as objective, and, thus, more persuasive (Commerford et al., 2022). Commerford et al. (2024) and Peecher et al. (2026) examined which factors impact the tendency of auditors to under-rely on AI. The findings indicate that auditors who provide input to the AI (Commerford et al., 2024) exhibit less under-reliance on AI. However, while providing input increases reliance overall, algorithm aversion persists and is shaped by perceived control, where auditors with low perceived control increase reliance when they receive advice from AI, and auditors with high perceived control remain relatively resistant to AI advice. In the same vein, Peecher et al. (2026) demonstrate that auditors who are affirmed in their abilities exhibit less under-reliance on AI, while auditors disaffirmed in their abilities exhibit stronger AI aversion (Peecher et al., 2026). This tendency arises because auditors who are reminded of their weakness and skill gaps feel more threatened by AI, exhibiting stronger aversion towards it (Peecher et al., 2026). As audit firms increasingly adopt AI in their audit process, such a tendency of individual auditors to discount AI evidence is problematic, as it could increase the likelihood of accepting biased or fraudulent information from clients when the contradictory evidence comes from an algorithm like AI, while such information would be rejected if contradictory evidence came from human colleagues, jeopardizing the audit quality (Commerford et al., 2022).

At the same time, other audit literature highlights the issue of auditors' over-reliance on AI. Particularly, Kokina et al. (2025) highlight risks of potential over-reliance of auditors on AI, which can lead to poor audit quality, especially if AI is flawed. They further emphasize the need for auditors to continuously exercise professional skepticism when interacting with AI, as well as for audit firms to support their skepticism through appropriate procedures and trainings (Kokina et al., 2025).

Whether auditors under-rely on AI or place excessive reliance on it, both behaviors may pose risks to audit quality if auditors rely disproportionately on either human or AI-generated information instead of critically evaluating audit evidence from both sources. Specifically, under-reliance leads auditors to discount AI-generated contradictory evidence and instead place greater weight on human-provided information, increasing the likelihood of accepting biased estimates and proposing insufficient audit adjustments (Commerford et al., 2022), while over-reliance exposes auditors to the risk of accepting flawed or biased AI outputs (Kokina et al., 2025), where both can result in inaccurate audit conclusions and reduced reliability of audit results, disturbing audit effectiveness.

4.3 AI-driven auditors' satisfaction

4.3.1 Decreased workload and enhanced job meaningfulness

While all the effects discussed above represent the demand for audit practice, which either intensifies auditors' job strain or disturbs audit effectiveness, the fifth identified effect of AI on audit practice represents a resource to audit practice, which supports auditors' work satisfaction. We identified that AI leads to *decreased workload and enhanced job meaningfulness* in the audit profession, where workload refers to the amount of work auditors perform in a specific period (Alghamdi, 2016), and job meaningfulness refers to the degree to which they experience their job as generally meaningful, valuable, and worthwhile (Hackman & Oldham, 1976). Although it might seem like two separate phenomena, the reviewed literature maps decreased workload and enhanced job meaningfulness as very closely interrelated, where AI-driven reduction in certain audit tasks enables greater engagement in value-adding activities, enhancing the perceived meaningfulness of auditors' work (Fotoh & Mugwira, 2025a; Kend & Nguyen, 2020). Thus, they are viewed as one effect. Within the AD-RFA, the *decreased workload and enhanced job meaningfulness* is conceptualized as resources for audit practice with individual-level outcomes. The reviewed literature examines the impact of AI on auditors' workload and perceived job meaningfulness, as well as its influence on additional factors that may enhance auditors' job satisfaction.

A consistent finding across the reviewed studies is that AI automates repetitive, highly structured, and time-consuming audit tasks, thereby reducing auditors' involvement in routine work. For example, a study by Vitali & Giuliani (2024) reveals that auditors perceive AI as a technology that decreases their workload and allows for a more equitable distribution of activities within the audit teams, mitigating work overload for individual professionals. The study additionally demonstrates that auditors perceive AI as reducing their involvement in routine, tedious tasks and, thus, creating the sense of "interesting work" (Vitali & Giuliani, 2024). Similar conclusions were reached in a study by Kend & Nguyen (2020) and Fotoh & Mugwira (2025), who highlight that AI reduces the time auditors spend on repetitive routine tasks, allowing them to focus on highly value-adding activities that require their critical judgment.

Taken together, AI's ability to reduce monotonous and repetitive audit tasks, eliminate auditors' work overload, and foster auditors' involvement in more meaningful value-adding tasks positions it as a resource to audit practice that improves job satisfaction on the individual auditor's level (Kawada et al., 2024). Therefore, this effect of AI is placed on the resource–individual level quarter of the AD-RFA. Research further explores whether AI brings additional improvements to the auditors' experience of their work. For example, Griffith et al. (2025) explored whether AI tools used for communication channels can improve auditors' psychological safety through perceived anonymity and, consequently, enhance their tendency to speak up about audit issues within audit teams. However, their findings show that the presence of such AI-enabled tools does not significantly increase auditors' psychological safety or their likelihood of speaking up.

4.4 AI-driven improvement to audit firms' effectiveness

4.4.1 Increased efficiency

The sixth identified effect of AI on audit practice is the *increased efficiency* it brings to the audit process. We conceptualize efficiency as the amount of time and other material or immaterial resources required to perform audit tasks, where reviewed studies used various proxies of audit efficiency, like audit report lag (Rahman et al., 2024), speed of the audit fraud identification (Christensen et al., 2025), or audit fee (Fedyk et al., 2022). The reviewed literature generally suggests that AI improves audit efficiency, consequently, enhancing audit effectiveness, which is the broad term that describes an audit firm's ability to fulfill its objectives and encompasses operational measures such as the efficiency of audit processes. Therefore, within the AD-RFA, this effect is mapped as a firm-level resource, as it enhances productivity and supports overall audit effectiveness. This section summarizes findings on AI impact on audit process efficiency.

The literature provides clear evidence that AI enhances audit efficiency. For instance, Li et al. (2024) show that an LLM-assisted framework for continuous auditing substantially improves the efficiency of payroll cross-verification. Specifically, by comparing manual completion of several audit steps, including document access, information search, and cross-checking, with AI (LLM)-enabled completion, they demonstrate that the manual completion takes around 3 minutes, while AI (LLM)-enabled completion of the same tasks takes less than 30 seconds, resulting in an 83 percent increase in speed (Li et al., 2024). Similarly, Christ et al. (2021) find that drone-enabled inventory audit procedures are far more efficient than traditional manual counting. Their results show that the technology-enabled inventory counting process reduced total counting time from hundreds of hours to fewer than 20 hours (Christ et al., 2021).

Evidence from experimental studies also suggests that AI can improve efficiency in judgment-based audit tasks. Christensen et al. (2025) report that auditors with access to generative AI complete fraud risk identification tasks more quickly than auditors without access, with the effect being especially strong for junior auditors, who achieve a 23 percent decline in the amount of time required to complete these tasks. In a similar vein, Föhr et al. (2023), focusing on sustainable assurance, conclude that the use of AI foundation models offers substantial efficiency gains in various audit tasks because results are produced within seconds, and validating AI output is less time-consuming than performing the audit steps manually without AI. Findings of qualitative research also support the view that AI enhances audit efficiency. For example, Vitali & Giuliani (2024), building on the interviews with the audit stakeholders, show that AI reduces effort on routine tasks and enhances audit speed. These findings are further supported by Fotoh & Mugwira (2025).

Interestingly, archival evidence on the AI effect on efficiency is more mixed. Fedyk et al. (2022) find preliminary evidence that firms investing in AI reach reduced audit workforces and increased productivity as measured by total fees per employee, which is consistent with improved efficiency. At the same time, Rahman et al. (2024) show evidence of a positive correlation between AI use by the audit firm and the length of the audit report lag in cases where audit clients are not using AI for their financial reporting, meaning that when audit firms are using AI, the time span between a company’s fiscal year-end and the date of the auditor's report increases (Rahman et al., 2024), indicating that audit teams require a longer time to complete engagements under such conditions. This evidence implies that efficiency gains from AI are not universal and may depend on the type of inputs audit teams receive from their clients.

4.4.2 Increased accuracy

The seventh, final, identified effect of AI on audit practice is the *increased accuracy* it enables among different audit procedures. Just as with the audit efficiency, the reviewed literature applied many different proxies of audit accuracy, including the amount of audit restatements (Fedyk et al., 2022), the task error rate (Christ et al., 2021), or the accuracy of fraud prediction (Lin et al., 2003), demonstrating the overall positive effect of AI on the audit accuracy. From the perspective of the AD-RFA, this effect is conceptualized as a firm-level resource, as it strengthens audit quality and the reliability of audit outcomes, enhancing audit effectiveness.

As previously mentioned, across the reviewed studies, it is seen that AI is frequently associated with improvements in audit accuracy, although this effect is not uniform across all contexts and technologies. Several studies indicate that AI can enhance the precision with which auditors identify misstatements, fraud risks, and reporting irregularities. For instance, Gu et al. (2024) demonstrate that fine-tuned AI models can generate more accurate and comprehensive audit solutions when appropriate interaction techniques, such as instruction learning, in-context learning, and chain-of-thought prompting, are applied, improving the accuracy of audit analyses and supporting better-informed auditor decisions. . Similarly, Fabian & Ratzinger-Sakel (2026) show that task-specific AI tools enhance the detection of missing or inaccurate disclosures in management reports while also improving the quality of audit documentation. At the same time, their findings demonstrate that inaccurate disclosure detection by AI is less effective for complex qualitative issues, such as misleading presentations (Fabian & Ratzinger-Sakel, 2026).

The positive impact of AI on audit accuracy is further discussed by qualitative research. Studies based on interviews with auditors indicate that AI tools enable auditors to examine entire transaction populations rather than relying primarily on sampling, allowing auditors to focus attention on transactions that are more likely to contain misstatements (Samiolo et al., 2024; Kend & Nguyen, 2020).

This finding is consistent with Li et al. (2024), who show that AI (LLM)-enabled frameworks enable full-population testing of audit evidence extracted from real-time textual sources, although, again, the extracted evidence is not fully error-free, as inaccuracies such as false positives and false negatives occur.

Empirical archival evidence also supports the argument that AI adoption is associated with higher audit accuracy. For example, Fedyk et al. (2022) report that AI investments by audit firms are linked to significant declines in the incidence of financial restatements, including material restatements and those related to accruals and revenue recognition, suggesting that AI contributes to more accurate audit outcomes. Similar findings are claimed by Rahman et al. (2024), who indicate that the adoption of AI by audit firms is associated with a lower probability of audit restatements, while Law & Shen (2025) show that audit offices employing AI employee, who are classified as such if their job title or job description involved AI-related words, produce audits of higher quality compared with offices without AI capabilities.

A bunch of studies specifically focus on generative AI and its effect on audit accuracy, suggesting that it improves the accuracy and effectiveness of certain audit tasks, particularly in fraud risk identification and analytical reasoning. Experimental evidence demonstrates that access to generative AI enables auditors to identify a greater number of relevant fraud risks (Christensen et al., 2025). Further, research shows that in some cases, fully automated generative AI models actually outperform human auditors in detecting fraud risk (Christensen et al., 2025) and brainstorming audit issues (Isack, 2024). Another experimental study by Bhaskar et al. (2024) illustrates that generative AI provides context-specific information that helps auditors better understand the implications of acquired audit evidence, which improves their judgment and ability to distinguish between audit issues and non-issues, increasing their tendency to speak up about identified issues.

Research further shows that various technologies categorized as AI-based contribute to significant improvements in audit accuracy. For instance, Christ et al. (2021) show that drone-enabled inventory audits combined with machine-learning counting algorithms reduce counting errors during the inventory audits while simultaneously producing higher-quality documentation. Similarly, Lin et al.

(2003) show that fuzzy neural network models – a type of AI-based technology – used for fraud risk assessment achieve significantly higher accuracy in identifying fraudulent financial reporting compared with traditional non-AI-based statistical models, while Wang et al. (2025) report higher predictive accuracy of an AI-based deep learning model in detecting financial statement fraud and identifying different fraud types compared with traditional fraud detection methods that do not rely on AI-based algorithms.

AI's positive impact on audit accuracy further improves trust between audit stakeholders and audit firms' reputation. For example, Osei-Assibey Bonsu et al. (2023) claims that AI reduces agency costs in audit practice by improving transparency, enabling real-time monitoring of firms' data, and limiting information asymmetry. In the same vein, Libby & Witz (2024) provide evidence that the use of AI in auditing mitigates public concerns that auditors' judgments are biased and enhances jurors' trust when the appearance of auditors' independence is compromised, while Fuchs et al. (2025b) claim that the use of AI in audit strengthens public confidence and perceived audit value among various stakeholders.

Despite these positive findings, several studies highlight important limitations that may constrain the impact of AI on audit accuracy. Some research indicates that machine learning models may produce large numbers of false positives in fraud detection tasks, which can reduce their practical usefulness and require careful interpretation by auditors (Wu et al., 2025). Generative AI tools may also generate inaccurate outputs due to hallucinations, outdated information, or insufficient contextual understanding (Fotoh et al., 2025; Föhr et al., 2023).

Overall, with few exceptions, most of the existing literature agrees that AI technologies have substantial potential to improve audit accuracy. However, it is evident that audit firms and individual auditors should exercise caution regarding potential limitations of AI, such as hallucinations and their possible implications for audit output.

4.5 Suggested avenues for future research

Overall, the majority of the reviewed literature emphasizes the benefits that AI brings to audit practice. For example, studies suggest that AI enhances the accuracy of audit analysis (Fabian & Ratzinger-Sakel, 2026; Gu et al., 2024), leads to a lower audit restatement rate (Fedyk et al., 2022; Rahman et al., 2024), and a higher level of fraud detection (Christensen et al., 2025). The literature also consistently reports that AI enhances the efficiency of the audit process (Christ et al., 2021; Li et al., 2024), consequently mitigating the auditors' workload, specifically in terms of the number of repetitive tasks auditors face (Vitali & Giuliani, 2024). At the same time, the review documents a range of challenges AI introduces to audit practice. First, AI compromises the ability of auditors to judge critically, meaning that auditors are losing the ability to appraise and validate AI-generated outputs (Fuchs et al., 2025a; Samiolo et al., 2024), which, consequently, compromises their professional judgment. Second, AI induces cognitive and mental load on auditors through inducing new professional expectations (Vitali & Giuliani, 2024) or disturbing their sense of professional security (Siddiqui & Raheman, 2025).

These insights deepen our understanding of AI’s dual role in enhancing and challenging audit practice, but also point to important avenues for future research. First, as demonstrated in the review, AI is affecting the work demands auditors face as well as their sense of job security. Prior research across industries links such factors to individuals' psychological outcomes and professional well-being, like heightened mental strain (Sweller, 1988, 1994), depression, anxiety, and emotional exhaustion (Llosa et al., 2018). At the same time, AI increases auditors’ sense of job meaningfulness and reduces workload, potentially mitigating these negative effects (Virtanen et al., 2011). Yet, despite AI's potential to affect auditors’ well-being, no research explicitly examines how interaction with AI at work impacts individual auditors' psychological outcomes, including their job satisfaction, job engagement, or burnout. Future research should explore whether such outcomes differ between auditors who actively use AI, those who do not, and those who anticipate its introduction, as such psychological outcomes may also arise from the expectation of upcoming AI adoption. Additionally, research should pay close attention to how firms and regulators can support individual auditors and facilitate sustainable AI integration at the individual level.

Second, existing literature highlights that AI use in audit practice leads to auditors' professional deskilling and loss of a comprehensive understanding of the audit process. Yet, the documentation of the ongoing deskilling is currently drawn exclusively from qualitative data and doesn’t provide quantifiable evidence of AI-driven auditors' deskilling and its effect on their judgments. Such a reliance on qualitative data calls for research employing alternative methodologies to determine whether measurable differences exist in the skills and knowledge of auditors who interact with AI compared to those who do not, which skills are most affected, and what the implications are for the audit quality. Additionally, future research should examine how audit firms can mitigate auditors' deskilling, for example, through training, task design, or management control. Research can also give more attention to the potential antecedents of deskilling – for example, by investigating how deskilling correlates with auditors' tendency to under- or over-reliance on AI output, the other effects identified within AD-RFA. Understanding these dynamics is critical to lessen the potential risks that deskilling can impose on audit output.

Third, as previously mentioned, the reviewed literature highlights concern regarding AI's effect on the auditors' judgment, indicating that auditors often do not judge critically when receiving input from AI, either under-relying on it by discounting accurate information (Commerford et al., 2022, 2024) or over-relying on it (Kokina et al., 2025) by accepting inaccurate outputs. However, no research has investigated what constitutes the appropriate level of auditors' professional judgment when cooperating with AI, and to what extent auditors can rely on it. Considering the 'black box' nature of AI, it is inherently hard or even impossible for its users to understand how its outputs are generated (Dourish, 2016; Lebovitz et al., 2022; Rai, 2020), which complicates their evaluation. Considering such a characteristic of AI, future research should investigate the extent to which auditors should be able to rely on AI-generated audit output and how their reliance should vary across different audit tasks. It should also examine how auditors can verify and challenge AI-generated outputs to ensure the appropriate level of audit accuracy, and what the implications are of various verification methods for the firm-level effectiveness.

Fourth, the reviewed literature provides mixed evidence regarding the overall impact of AI on the reliability of audit results and the level of assurance that audit firms can provide to their clients. While existing literature largely agrees that AI improves the accuracy of audit procedures, it also warns the practice about AI's negative impact on the auditors' judgment, which, in combination with AI imperfections like hallucinations, could jeopardize audit results. Therefore, it appears that AI simultaneously improves and jeopardizes audit output. Yet, there is little understanding of how these two effects interact and what the ultimate consequences are for audit practice. This highlights the need for future research to provide clarity on what are the ultimate consequences of AI introduction for the reliability of audit results and the level of assurance that audit firms provide. Additionally, considering the implications of AI for auditors' judgment, future studies should assess the relative effectiveness of human–AI collaboration compared to full AI-enabled automation in achieving reliable audit results.

Last, and more broadly, this review reveals that AI introduces a complex system of interrelated demands and resources within audit practice. Future research should move beyond examining isolated AI effects on audit practice and instead adopt a more integrative perspective that captures the interaction between these effects. For example, from the review, we see that while AI improves audit accuracy, it may also impair auditors' judgment and, together with imperfections such as hallucinations, jeopardize audit outcomes. As a result, AI simultaneously enhances and threatens audit reliability, yet there is little understanding of how these two effects interact and what the ultimate consequences are for audit practice. This highlights the need for future research to provide clarity on what are the ultimate consequences of AI introduction for the reliability of audit results and the level of assurance that audit firms provide. Moreover, future studies could explore hierarchical relationships between outcomes, such as whether individual-level effects (e.g., stress, job satisfaction) translate into firm-level outcomes, including audit quality and efficiency, or horizontal relationships, exploring whether identified effects are each other's antecedents or consequences. Finally, it would be valuable to investigate how the seven identified effects of AI on audit practice evolve as AI technologies continue to develop. The avenues for future research that emerge from the literature review are summarized in Table 1.

Identified research gap	**Suggested research questions for future studies**
Lack of research on AI's impact on auditors' psychological outcomes and professional well-being.	• How does interaction with AI affect auditors' mental state? • How does interaction with AI affect auditors' professional well-being, including their job satisfaction, job engagement, and burnout? • Do these outcomes differ between auditors who use AI, do not use AI, or anticipate its upcoming adoption?

	• How can firms and regulators support auditors' well-being during AI integration?
Lack of quantitative evidence on AI-driven deskilling of auditors.	• Are there measurable differences in skills and knowledge between auditors who use AI and those who do not? • Which auditor skills are most affected by AI-driven deskilling, and to what extent? • What are the implications of auditors' deskilling for overall audit quality? • How can audit firms mitigate auditors' deskilling (e.g., through training, task design, or management control)? • What are the antecedents and mediators of AI-driven auditors' deskilling? How does it relate to the effects identified within the AD-RFA?
Lack of understanding of the appropriate level of auditor reliance on AI and AI verification methods.	• What constitutes an appropriate level of auditor's reliance on AI-generated outputs? • How should auditors' reliance on AI vary across different audit tasks? • How can auditors effectively verify and challenge AI-generated outputs? • What are the implications of various verification methods for the firm-level effectiveness?
Lack of integrative research examining the interaction between the multiple effects of AI on audit practice.	• How do the different effects of AI on audit practice interact with each other? • What are the ultimate consequences of AI adoption for the level of assurance provided by audit firms? • To what extent can AI-driven accuracy gains compensate for impaired auditor judgment and professional deskilling? • Do improvements in auditors' work experience offset the increased cognitive load associated with new skill requirements and concerns about professional obsolescence? • How do individual-level outcomes (e.g., stress, job satisfaction) translate into firm-level outcomes, such as audit quality and efficiency? • What are the horizontal relationships between the identified effects of AI on audit practice (e.g., are certain effects antecedents or consequences of others)? • How do the identified effects of AI on audit practice evolve as AI technologies continue to develop?

Table 1: Identified research gaps and recommended research questions

5 Discussion and Conclusion

The audit profession is rapidly embracing AI, transforming practice at multiple levels, from individual auditors' work experiences to the assurance provided to society. To understand the most significant effects of AI on audit practice, together with the benefits and challenges they bring, we develop the AI Demands-Resources Framework for Auditing, which allows us to position all the effects of AI as demands or resources to audit practice and estimate their outcomes for individual auditors and the audit firms. AI is considered a demand when it imposes additional material or immaterial (physical or mental) costs on audit practice, or as a resource when it reduces job strain auditors face and facilitates the attainment of organizational objectives (Bakker & Demerouti, 2007). We systematically selected 31 top-ranked and the most newly emerged studies about AI in audit practice. We synthesized the findings, reporting both comparable and contradicting results, which allow us to create a comprehensive overview of existing knowledge about how AI is affecting audit practice.

The first main insight of this review relates to various widely-reported benefits of AI on the audit process. The literature shows that AI enhances audit quality by reducing human error, improving fraud detection, and enabling the analysis of full transaction populations rather than samples (Fedyk et al., 2022; Gu et al., 2024; Samiolo et al., 2024). These improvements are associated with lower audit restatement rates and more reliable audit outcomes (Rahman et al., 2024). What is more, AI increases audit efficiency by automating repetitive and time-consuming tasks, allowing auditors to focus on more complex, judgment-intensive activities (Christ et al., 2021; Li et al., 2024; Vitali & Giuliani, 2024). This highlights that AI is, in general, very useful and helpful for audit firms to accelerate their overall effectiveness – the ability to fulfil their organizational objective of providing timely and trustworthy assurance.

Second, this review demonstrates that the integration of AI into audit practice has the potential to significantly impact auditors' experience of their work and its psychological consequences. By creating a shift in the skills required from auditors and creating a sense of job uncertainty, AI imposes additional mental load on individual auditors. Simultaneously, AI is decreasing auditors' workload and involvement in tedious tasks (Vitali & Giuliani, 2024), allowing them to focus on more interesting, value-adding work (Fotoh et al., 2025a.). Such effects of AI function as both resources and demands for the auditors, potentially intensifying their job strain or, on the contrary, increasing their job satisfaction (Bakker & Demerouti, 2007). However, most research gives very little attention to how such effects actually materialize. Considering the rapid AI implementation within audit practice, it will be very relevant to investigate how cooperation with AI across various audit tasks impacts auditors' mental state and professional well-being.

The third insight relates to developments in the auditors' professional judgment when interacting with AI. The reviewed literature shows that AI overtakes certain audit steps and generates audit evidence on its own, changing the way audit work is structured, including the types of tasks auditors are involved in, and the sources of audit evidence they receive. Considering these changes, auditors, when interacting with AI, may be limited in exercising professional skepticism and critical judgment. This transformation creates two potential consequences, where auditors either unjustifiably discount AI evidence (Commerford et al., 2022, 2024; Peecher et al., 2026) or over-rely on it (Kokina et al., 2025), where both behaviours are suboptimal for audit firms' effectiveness. In addition, AI is restraining auditors' professional development and their ability to judge critically as part of it (Fuchs et al., 2025a), while simultaneously increasing auditors' involvement in more complex audit tasks that require critical judgment. Such inconsistency was previously acknowledged in the literature (e.g., Samiolo et al., 2024), however, little research has addressed how auditors' judgment can be supported and retained when collaborating with AI. We suggest that audit firms and regulators define clear guidance on what it means to exercise critical judgment and professional skepticism when cooperating with AI. For example, guidance could clarify whether AI outputs can be relied upon directly as audit evidence or whether they must be validated, and how such validation should be performed. This said, future research should support practice in developing the most effective guidance on AI collaboration that ensures a reliable audit process.

Last, this review reveals insights about the broader impact of AI on audit practice. AI creates both demands and resources to audit practice, contributing both to the strain and motivation of individual auditors, as well as improving while simultaneously jeopardizing audit effectiveness and reliability. It is important that future research doesn't focus on separate dimensions of the AI effect of audit practice, but examines the interaction between the various identified effects of AI on audit practice, such as whether AI-driven accuracy gains alleviate the consequences of the disturbed judgment and deskilling, or whether auditors' improved work experience offsets the cognitive load created by new skill requirements or fear of professional obsolescence. Future research could also explore hierarchical effects, for instance, whether individual-level outcomes such as strain, satisfaction, eventually translate into firm-level effectiveness, including the accuracy of its outputs and the efficiency of its process. Additionally, it could be interesting to analyze how all the identified effects evolve as AI progresses and develops.

This review is subject to certain limitations. First, we synchronize and aggregate the findings of the reviewed literature without taking into account the contextual differences, like the country where each study was conducted or what specific type of AI was considered. In line with our definition of AI as "a broad class of technologies that allow a computer to perform tasks that normally require human cognition" (Tambe et al., 2019, p. 16), some of the reviewed studies treat AI as a broad concept (Commerford et al., 2022, 2024; Fedyk et al., 2022; Kokina & Davenport, 2017; Law & Shen, 2025), while others focus on more specific subcategories, such as generative AI (Christensen et al., 2025; Fotoh et al., 2025; Bhaskar et al., 2024), or on a particular technology type such as large language models (LLMs) (Fotoh & Mugwira, 2025a; Li et al., 2024) or other AI-based technologies. In addition, the reviewed studies examine different applications of AI in audit practice. Some studies focus on AI for the analysis of client data (Lin et al., 2003; Rahman et al., 2024; Wang et al., 2025; Wu et al., 2025), while others consider AI as a technology used within audit teams, for example, for internal communication (Griffith et al., 2025). Other studies do not focus on specific applications of AI but instead examine its use at the firm level, measuring AI adoption based on whether the firm hires professionals whose roles involve AI (Fedyk et al., 2022; Law & Shen, 2025). This approach may yield conclusions that appear universally applicable across different types of AI and their various applications within audit practice, but which in fact depend on specific contextual conditions.

Second, an important limitation lies in the search approach that was applied. Considering the wide range of different AI-based capabilities, relevant studies could have been missed if they do not explicitly use the term "Artificial Intelligence" or "AI", which was applied for the search string, but still explore the impact of AI-based technology on audit practice. The discussed limitations provided additional interesting opportunities for future research that were not initially addressed based on the identified research gaps. Specifically, future literature reviews could explicitly focus on specific types of AI of interest and their application within audit practice.

Overall, this study shows that AI imposes significant effects on audit practice, which act as both demands and resources, bringing benefits and challenges to individual auditors and audit firms. By developing the AD-RFA framework, we provide a structured lens to understand the dual nature of AI, offering valuable insights and research directions for academic and practice.

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Appendix

Appendix 1

Authors	Authors	Journal or Source	Data collection method	AI type	Relation to the identified AI effect	Key findings
Bhaskar et al.	2024	SSRN	Experiment	Generative AI	Accuracy	Generative AI improves auditors' understanding of audit evidence and helps them better distinguish real issues from non-issues, increasing appropriate voice decisions.
Christ et al.	2021	Review of Accounting Studies	Design science research; Interview	ML	Efficiency	Drone-enabled inventory auditing combined with ML counting algorithms reduces counting time compared with manual procedures.
					Accuracy	Drone-enabled inventory audits combined with ML counting algorithms reduce error rates and can match or improve counting accuracy compared to manual inventory audits.
Christensen et al.	2025	SSRN	Experiment	Generative AI	Efficiency	Generative AI helps both novice and experienced auditors identify fraud risks faster, allowing junior auditors to achieve a 23 percent decline in the amount of time required to identify fraud risks.
					Accuracy	Generative AI helps auditors identify more fraud risks and can, in some cases, outperform human auditors in fraud detection.
Commerford et al.	2022	Journal of Accounting Research	Experiment	AI	Auditors' under-reliance on AI	Auditors display algorithm aversion by discounting contradictory evidence more heavily when it comes from AI rather than a human specialist, especially when human evidence appears objective.
Commerford et al.	2024	Contemporary Accounting Research	Experiment; Interviews	AI	Auditors' under-reliance on AI	Auditors exhibit algorithm aversion, and while allowing auditors to provide input increases reliance on AI advice overall, it does not eliminate algorithm aversion, with the effect mainly driven by auditors with low perceived control, whereas high-control auditors remain relatively resistant to AI advice.
Fabian & Ratzinger-Sakel	2026	Journal of Information Systems	Survey	AI	Accuracy	Task-specific AI enhances the detection of missing or inaccurate disclosures in management reports while also improving the quality of audit documentation. At the same time inaccurate disclosure detection by AI is less effective for complex qualitative issues, such as misleading presentations.
Fedyk et al.	2022	Review of Accounting Studies	Archival data; interviews	AI	Accuracy	Audit firms' AI investments are associated with fewer restatements, including material and accrual-related restatements, indicating higher audit quality.
					Efficiency	Firms investing in AI reach reduced audit workforces and increased productivity as measured by total fees per employee, which is consistent with improved efficiency.
					Professional obsolescence	Audit firm's investments in AI capabilities are associated with a decrease in the number of audit employees employed by that firm a few years after the investments, with the association being especially strong for junior auditors.
Föhr et al.	2023	SSRN	Design science research	Generative AI	Efficiency	Generative AI produces sustainability audit results quickly and substantially reduces the effort needed compared with fully manual procedures.
					Accuracy	Generative AI may produce hallucinated content.

Authors	Authors	Journal or Source	Data collection method	AI type	Relation to the identified AI effect	Key findings
Fotoh & Mugwira	2025	International Journal of Accounting Information Systems	Survey; prompts evaluation	LLM	Workload and job meaningfulness	Auditors perceive LLMs as useful for routine tasks, redirecting of auditors' attention towards value-added activities and complex tasks requiring judgment.
					Efficiency	Non-Big Four auditors perceive LLMs as time-saving tools and support routine audit work.
Fotoh et al.	2025	SSRN	Survey; textual analysis	Generative AI	Accuracy	Generative AI is prone to hallucinations and can produce incorrect and fabricated output, often with false justifications.
Fuchs et al.	2025a	SSRN	Interviews	AI	Auditors' deskilling	AI changes audit work structure and poses the risk of diminishing the scope of knowledge-intensive professional work that may lead to the auditors' deskilling and hindered professional judgment in the longer-term.
Fuchs et al.	2025b	SSRN	Interviews	AI	Accuracy	The use of AI in audit strengthens public confidence and perceived audit value among various stakeholders.
Griffith et al.	2025	Auditing: A Journal of Practice & Theory	Experiment; Survey	AI	Workload and job meaningfulness	AI-enabled anonymous communication tools are designed to create a safer space for auditors to speak up about audit issues. However, these tools do not significantly improve auditors' psychological safety or their willingness to speak up about audit issues.
Gu et al.	2024	International Journal of Accounting Information Systems	Prototyping	Generative AI (specifically foundation models, e.g., GPT-4, DALL-E, LaMDA)	Accuracy	Fine-tuned AI models produce more accurate and comprehensive audit-related outputs and can support better-informed auditor decisions.
Isack	2024	SSRN	Experiment	Generative AI (specifically GPT-4)	Accuracy	GPT-4 sometimes outperforms human auditors in brainstorming-type tasks, however it struggles with some complex audit concepts.
Kend & Nguyen	2020	Australian Accounting Review	Interviews; focus Group	AI	Auditors' deskilling	While AI automates routine audit tasks and allows greater transaction coverage, it also changes the nature of auditors' work and may reduce reliance on traditional experiential learning.
					Workload and job meaningfulness	AI automates routine tasks and allows auditors to focus on more critical, judgment-intensive aspects of the audit.
					Accuracy	AI enables auditors to analyze more transactions and reduce reliance on sampling, providing higher levels of assurance.
Kokina et al.	2025	International Journal of Accounting Information Systems	Interviews	AI	Auditors' over-reliance on AI	Auditors may over-rely on AI, potentially impairing audit quality if systems are flawed.

Authors	Authors	Journal or Source	Data collection method	AI type	Relation to the identified AI effect	Key findings
Koreff et al.	2023	Journal of Information System	Interviews	AI	Auditors' deskilling	Healthcare auditees sometimes perceive auditors who rely on AI as lacking the necessary expertise and professional judgment to interpret audit evidence, substituting the lack of judgment with AI use.
Law & Shen	2025	Management Science	Archival data; interviews	AI	Cognitive load from skills shift	AI adoption in audit firms increases demand for auditors' soft skills, such as cognitive ability, efficiency, and communication, due to greater involvement in analytical work and cross-team collaboration, highlighting the need for professional training.
					Accuracy	Audit offices that hire AI employees (an employee is classified as an AI employee if the job title or job description contains any of the AI keywords) produce higher audit quality than those without AI employees.
					Professional obsolescence	The use of AI by audit firms is associated with a larger number of audit jobs available among associated firms.
Li et al. (2024)	2024	SSRN	Design science research	LLM	Efficiency	LLM-assisted auditing framework reduces payroll cross-verification time.
					Accuracy	LLM-assisted auditing framework enables full-population testing of audit evidence extracted from real-time textual sources, although, again, the extracted evidence is not fully error-free, as inaccuracies such as false positives and false negatives occur.
Libby & Witz	2024	Contemporary Accounting Research	Experiment	AI	Accuracy	AI use helps preserve perceptions of auditors' objectivity and trust, reducing the negative effect of apparent independence conflicts on jurors' negligence judgments.
Lin et al.	2003	Managerial Auditing Journal	Archival data; prototyping	FNNs	Accuracy	A fuzzy neural network outperforms a traditional logit model in predicting fraudulent financial reporting.
Osei-Assibey Bonsu et al.	2023	Journal of Applied Accounting Research	Survey	AI	Accuracy	AI reduces agency costs in audit practice by improving transparency, enabling real-time monitoring of firms' data, and limiting information asymmetry.
Tiberius et al.	2019	Journal of International Accounting, Auditing and Taxation	Delphi method	AI	Professional obsolescence	Audit users do not expect auditors' judgment to become obsolete or for automated audit procedures to surpass manual ones in trustworthiness.
Peecher et al.	2026	Contemporary Accounting Research	Experiment	AI	Auditors' under-reliance on AI	Disaffirmation triggers auditors' AI aversion, causing them to defensively discount specialist advice, whereas self-affirmation has high potential to mitigate AI aversion.
Rahman et al.	2024	Managerial Auditing Journal	Archival data	AI	Efficiency	When only audit firms use AI, audit report lag decreases, suggesting lower audit efficiency. However, when both audit firms and clients use AI, audit report lag also decreases, indicating higher audit efficiency.
					Accuracy	AI adoption is associated with a lower likelihood of audit restatement.
Samiolo et al.	2024	Contemporary Accounting Research	Interview	AI, ML	Auditors' deskilling	AI disturbs auditors' learning process, putting junior auditors, who no longer perform routine tasks at risk of not developing a holistic perspective and critical judgment, with deskilling risks potentially extending to auditors at all experience levels.

Authors	Authors	Journal or Source	Data collection method	AI type	Relation to the identified AI effect	Key findings
					Accuracy	AI expands auditors' capabilities by scanning full populations of transactions, and reducing human error.
Siddiqui & Raheman	2025	International Journal of Auditing	Qualitative thematic analysis	AI	Professional obsolescence	Stakeholders perceive technological developments such as AI as reducing the long-term relevance of the auditing profession and making traditional auditing obsolete.
Vitali & Giuliani	2024	International Journal of Accounting Information Systems	Interview	AI	Cognitive load from skills shift	Auditors expect that AI adoption will increase the demand for auditors' technical skills, particularly in IT and computer science, which many practitioners currently lack.
					Workload and job meaningfulness	Auditors perceive AI as automating routine and time-consuming audit tasks, which reduces workload, improves the distribution of work within audit teams, and allows auditors to focus on more interesting tasks.
					Efficiency	Auditors expect AI and related technologies to improve efficiency in their daily activities.
Wang et al.	2025	Journal of Forensic Accounting Research	Design science research; Prototyping	Deep neural networks (DNNs)	Accuracy	A deep learning fraud prediction system achieves high predictive accuracy compared with traditional fraud detection methods that do not rely on AI-based algorithms, and can identify different types of fraudulent activity.
Wu et al.	2025	Journal of Accounting Literature	Archival data	Machine learning (ML)	Accuracy	ML models can support fraud detection, but their practical value is constrained by false positives and inconsistent superiority over traditional logistic regression.

Appendix 1: Overview of reviewed studies and their contribution to the identified AI effects in audit practice