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AI in auditing: Drivers and barriers to its adoption and the sociomaterial reconfiguration of the auditor's role

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Abstract

Research Question: What are the drivers and inhibitors of Artificial Intelligence (AI) use in auditing, and how does AI reconfigure the auditor's role?
Motivation: The adoption of Artificial Intelligence (AI) in auditing has advanced rapidly, transforming processes, resources, and professional practices.
Idea: The analysis is grounded in sociomateriality theory and examines how the introduction of AI reconfigures the auditor's role, posing new challenges.
Data: The study is based on a Systematic Literature Review (SLR) of 43 studies.
Tools: The sociomaterial lens is used to analyze the interaction between auditors and AI tools, considering both technological capabilities and professionals' engagement and adaptation.
Findings: The results indicate that AI adoption in auditing is driven by efficiency, accuracy, real-time auditing, Big Data analytics and standardization. However, barriers such as resistance to change, algorithm aversion, heuristics and biases, transparency, expertise and training gaps, and complexity limit the full adoption of these technologies. This process is dynamic and ongoing: as technology evolves, organizational practices and arrangements also transform, rebalancing functions and responsibilities.
Contribution: From this perspective, the benefits of AI in auditing can be more effectively realized when organizational practices support interaction between auditors and AI tools.

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Therefore, the sociomaterial lens allows us to observe that the auditor's reconfiguration occurs dynamically and continuously, relying both on the evolution of technological capabilities (material agency) and on professionals' engagement and adaptation (social agency).

Keywords: artificial intelligence, auditing, drivers, barriers, agency, sociomateriality

JEL codes: M42, O33

1. Introduction

Artificial Intelligence (AI) is profoundly transforming the fields of accounting and auditing by enabling more accurate and rapid analyses of large volumes of data, with expectations that 99% of companies will use AI in their financial reporting within the next three years (KPMG, 2024). The Big Four accounting firms have made substantial investments in developing new AI tools. Recent evidence indicates investments in the billions of dollars (Atalaia, 2025). In addition to large audit firms, AI-focused startups are also attracting significant funding to develop sector-specific solutions – for example, DataSnipper (Singh, 2024).

Emerging technologies are not a new phenomenon in auditing; generally, the goal of such tools has been to automate procedures, expand scope, shorten timelines, and improve overall quality. This concept is known as Auditing 4.0 (Dai & Vasarhelyi, 2016). The integration of AI into auditing is revolutionizing the industry by enabling greater efficiency, accuracy, and process automation, while allowing auditors to focus on strategic analyses and decision-making (PricewaterhouseCoopers, 2024). The success of this integration, however, hinges on a balance whereby technology serves to augment human capabilities, since automation, despite its efficiency, does not replace the professional experience and skepticism essential to the profession (Anwar, 2024).

Generative AIs, such as ChatGPT and BARD, have been widely adopted, with estimates indicating that 41% of audit teams were using them by 2024 (Gartner, 2024). This integration signals significant changes in how audit functions operate, enabling more efficient analyses of complex data sets and facilitating more informed decision-making processes. As a result, traditional audit methods are being impacted in various ways, given the advancement of algorithms capable of performing tasks previously reserved exclusively for humans (Almufadda & Almezeini, 2022).

Despite these technological transformations, the core purpose of auditing remains unchanged: to provide an opinion on the credibility of financial statements to inform reliable decision-making. Moreover, auditing is an information-intensive activity that encompasses the collection, organization, processing, evaluation, and presentation of data, commonly based on robust judgments concerning various aspects of the financial statements (Omoteso, 2012). With the advancement of AI and other digital technologies, audit methods are changing significantly, but the fundamental objectives and role of the auditor remain the same, with technology acting as a 'team member' in the audit process (Tiron-Tudor & Deliu, 2022).

AI performativity redefines the auditor's role, shifting from executing traditional tests to becoming an increasingly analytical, strategic professional engaged in high-value tasks, working alongside intelligent machines to monitor and improve their performance and results (Holmes & Douglass, 2022). As this process advances, the expression "know your clients" serves as an analogy for "know your data," since the ability to analyze entire data populations in real time requires auditors to develop analytical competencies inherent to the technology to oversee AI systems (Khan, 2017).

In this context, the interaction between users and technologies alters organizational behavior, requiring breaks from old habits and adaptations of systems, especially those related to decision-making (van Rijmenam & Logue, 2021). Different organizations respond to technological changes in distinct ways, influenced by factors such as environment and the type of technology adopted (Öztürk, 2021; Leonardi *et al.*, 2012). To analyze this dynamic, sociomateriality theory, developed by Orlikowski and Scott (2008), posits an inseparable relationship between organizational practices and technology. In this study, we employ sociomateriality theory to explain how the incorporation of AI into auditing alters technical processes and reconstructs professional practices, highlighting a new form of shared agency between humans and algorithms. Therefore, our objective is to identify the factors that impact AI use in auditing through the lens of sociomateriality theory. Accordingly, we seek to address the following research question: (i) which factors have been identified in the literature as determinants of the adoption and use of AI in auditing in light of sociomateriality; (ii) which factors constitute barriers, that is, those that hinder the full utilization of AI tools in auditing; and (iii) which gaps can be identified in this literature from this theoretical perspective.

The motivation for this study is threefold. First, this analysis contributes to the emerging literature on the impacts of AI technologies on the profession (Liao *et al.*, 2024; Almufadda & Almezeini, 2022; Zhang *et al.*, 2022). Identifying drivers and barriers expands existing knowledge and offers practical guidance for firms and policymakers to implement and use this technology with best-in-class governance practices.

Second, IT is a driver of audit quality, and in the case of AI, the benefits are also well documented (Fedyk *et al.*, 2022). Since audit quality is a central focus of investigation (Francis, 2024), identifying what prevents audit firms from adopting or intensively using AI is essential to understanding the measures that must be taken to overcome these barriers. Auditing serves a social interest function, which makes it imperative that auditors are equipped with the tools that enable them to produce higher-quality work.

Finally, previous studies have addressed aspects related to the integration of AI into auditing, but to our knowledge, none have specifically explored the factors from a sociomateriality perspective. Thus, the findings provide a more comprehensive and in-depth view of AI use in auditing, moving beyond changes in technical processes and professional practices to analyze a new form of shared agency. We differentiate ourselves by adopting the sociomateriality theory lens, seeking to explore how AI reconfigures relationships and practices in auditing. Autonomous agents, such as AI, operate as tools and also assume performative and independent roles, profoundly transforming organizations (van Rijmenam & Logue, 2021). This approach strengthens the theoretical foundation of our research and paves the way for future investigations by proposing a research agenda, enriching the debate on AI adoption and its impacts in auditing.

The rest of the article is organized as follows: Section 2 provides definitions of the audit process, AI, and sociomateriality. Section 3 describes the methodology applied in the SLR. Section 4 highlights the factors that most impact the studied relationship and develops an analysis from the sociomateriality perspective, as well as proposing suggestions for future research. Finally, Section 5 concludes the study, synthesizing the main contributions and implications of the findings.

2. AI and auditing

2.1 The audit process

Auditing is an examination conducted by a competent and independent individual, involving the collection and evaluation of evidence regarding specific information, with the objective of determining and communicating the extent to which that information complies with predefined criteria (Elder *et al.*, 2020). Understanding this process is fundamental to identifying the auditor's role and the benefits of AI applications in this field (Almufadda & Almezeini, 2022). The audit process typically comprises four phases: engagement acceptance; audit planning and identification and assessment of material misstatement risks; additional audit procedures: risk response through control tests and substantive tests; and completion of the engagement and issuance of the audit opinion.

Before engagement acceptance, the auditor assesses the feasibility and risks associated with taking on a new client or continuing an existing relationship. In this phase, AI has the capability to collect, aggregate, and examine large volumes of data from various external sources. AI then incorporates the client's organizational structure, operational methods, and financial systems to estimate an initial risk level (Issa *et al.*, 2016). Following the first phase is planning, where the overall strategy and scope of the audit are defined. The primary objective of this phase is to identify and assess the risks of material misstatement in the financial statements, whether due to fraud or error. To this end, AI assists by using text-mining and image-recognition techniques to analyze flowcharts, narratives, and questionnaires provided by the client (Issa *et al.*, 2016).

The next step in the audit process is the risk response, where tests are applied to obtain sufficient and appropriate evidence regarding the reliability of the information. Essentially, the effectiveness of the entity's internal controls in preventing or detecting misstatements is evaluated through control tests, and substantive tests are performed to detect material misstatements directly in account balances and transactions. Substantive procedures may be of two types: tests of details and substantive analytical procedures. In this phase, an AI-based continuous control monitoring system can examine the entire population of records to identify any control failures and report them (Issa *et al.*, 2016). Additionally, instead of performing periodic tests on a sample of transactions, AI can continuously examine the entire population (Sun, 2019; Issa *et al.*, 2016).

In the final stage of the audit engagement, the auditor evaluates the collected evidence to form an opinion on whether the financial statements are free of material misstatement and presented in accordance with the applicable financial reporting framework. The opinion is expressed in a report, which is the final product of the engagement, communicating the auditor's conclusions to stakeholders. In the traditional process, the auditor issues a categorical opinion (unmodified, qualified, adverse, etc.). With AI, the audit report can become continuous (for example, on a scale of 1 to 100) instead of categorical (Issa *et al.*, 2016). Moreover, according to Sun (2019), a deep-learning AI model can review debt contracts, attorney letters, and financial statements to ensure appropriate presentation and disclosure, ultimately aiding in forming the auditor's opinion.

2.2 Artificial intelligence

AI is defined as "the ability of computers or other machines to exhibit or simulate intelligent behavior" ("Artificial intelligence", 2024). The latest definitions focus on software designed to perform tasks previously exclusive to human intelligence, particularly through machine learning for analyzing large volumes of data.

The field of artificial intelligence (AI) encompasses a set of subfields and techniques that differ both in how they represent knowledge and in the type of learning they perform, among which expert systems, artificial neural networks (ANNs), machine learning (ML), and deep learning (DL) stand out, as well as natural language processing (NLP), large language models (LLMs), and generative AI (GenAI) applications.

Traditionally, expert systems operate based on rules and codified knowledge to replicate reasoning within specific domains and may, in certain cases, achieve results comparable to those of human experts (Almufadda & Almezeini, 2022; Ling-Fang, 2010). In contrast, ANNs adopt a logic inspired by the human brain and have proven effective in pattern recognition, in addition to constituting one of the historical foundations of applications in auditing (Koskivaara, 2000; Ling-Fang, 2010). ML expands this approach by encompassing algorithms capable of learning from data and generating predictions, classifications, and pattern detection through supervised, unsupervised, and reinforcement learning approaches (Chen, 2019).

Within this same context, DL corresponds to a subset of ML that employs multi-layer neural networks, enabling the processing of more complex data and contributing to advances in automation and fields such as computer vision (Paluszek & Thomas, 2020). In the textual domain, NLP allows systems to interpret human language, which is particularly relevant for auditing when extracting, organizing, and analyzing information contained in unstructured documents (Almufadda & Almezeini, 2022; Tiron-Tudor & Deliu, 2022). LLMs, in turn, represent a recent development that leverages deep neural networks to enhance the quality of text processing and language generation, with examples such as GPT and BERT (Kalyan, 2024). Finally, GenAI focuses on generating new content, such as text, images, and audio, and has been expanding the range of organizational applications, including code generation and conversational support. In this context, models such as ChatGPT incorporate multimodal capabilities (text and image) and reinforce the potential for use in natural language tasks (Feuerriegel *et al*., 2024; Kalyan, 2024).

2.2.1 Artificial intelligence in auditing

The Big Four have stood out in the use and application of AI tools in the performance of audit work. KPMG has been reshaping its functions by enabling continuous auditing and more granular risk assessment through specific platforms developed for this purpose (Stöckle, 2024). According to them, the use of algorithms trained to score transactions makes the process more efficient, while also incorporating ethical governance elements to ensure trust and transparency in the use of these technologies. PwC expands this notion by creating agents capable of monitoring large volumes of data in real time, allowing the immediate identification of distortions (Horlin, 2025).

Deloitte emphasizes that AI does not replace human judgment but rather enhances it by automating tasks and allowing auditors to focus on analytical assessments, creating a synergy between human and artificial intelligence (Deloitte, 2024). EY, in turn, has made continuous investments in developing the digital skills of professionals in order to enable auditors to act as critical validators in this increasingly automated setting (EY, 2026).

This understanding that the future of auditing involves organizing AI tools to enhance, rather than replace, the auditor's judgment has been discussed in several studies. In an essay with five mini case studies, Lin and Maginnis (2025) highlight that AI functions as a copilot in the external audit workflow, generating efficiency in various tasks, so that its sustainable adoption depends on governance and mandatory human review. This conclusion can be observed in a specific LLM model, such as ChatGPT, used to support auditors, provided that the risks associated with the use of the technology are properly controlled (Otero & Agu, 2025).

In this sense, generative AI is redefining auditing, but its adoption still faces significant challenges related to various factors (Zhang & Zhou, 2026). The main conclusion is that the future of the profession will be marked by integration between humans and machines, requiring new skills and a redefinition of the auditor's role (Gambhir *et al*., 2025).

2.3 Sociomateriality theory

Sociomateriality theory, first discussed by Orlikowski (2007) and Orlikowski and Scott (2008), asserts that materiality, physical and digital properties such as artifacts and technologies, is inseparably intertwined with the social, such that both co-constitute each other. This perspective is essential for understanding how organizational practices emerge and configure through dynamic, context-specific sociomaterial assemblages, where the social and the material are interdependent (Orlikowski and Scott, 2008; Orlikowski, 2007). Digital tools exemplify this interdependence by blending technological and social elements in many phenomena (Cecez-Kecmanovic *et al.*, 2014).

In the sense, Leonardi *et al.* (2012) and Leonardi (2013) complement this approach, albeit with differences. In these studies, the social and the material are initially distinct but become interdependent through a process called imbrication. They introduce the concepts of material agency, referring to the technology's capacity to act based on its properties, and social agency, which involves coordinated human action in response to technology (Leonardi, 2013; Leonardi *et al.*, 2012). Material agency operates through performativity but without its own intentions, while humans ascribe agency to objects by using them (Barad, 2003).

Moreover, Leonardi (2013) also explores critical realism, which regards the social and the material as distinct entities that become interdependent in practice. Unlike the agential realism of Orlikowski and Scott (2008), which treats the social and the material as inseparable, critical realism recognizes the temporal evolution of sociomaterial practices, facilitating empirical research.

Strong sociomateriality, proposed by Jones (2014), drawing on Barad (2003), argues that social and material entities do not exist independently but emerge together through practices. In this context, agency is distributed between humans and nonhumans, surpassing dualistic views (Jones, 2014; Kautz & Plumb, 2016). The concept of intra-action, introduced by Barad (2003), describes how these entities are defined and differentiated through their practices.

Sociomateriality theory clarifies the role of technology in organizations by highlighting its constitutive interactions. Orlikowski (2007) states that technology is shaped by and shapes human actions, although its material properties impose constraints, especially when integrated into systems. In the context of AI, these interactions take new forms. Van Rijmenam and Logue (2021) introduce the concept of artificial agency, defined as the capacity of AI agents to act autonomously without human intervention, distinguishing them from traditional user-controlled technologies (Leonardi, 2013). These artificial agents operate independently, reconfiguring work practices and organizational decisions (van Rijmenam & Logue, 2021). This reconfiguration capability stems from an agency that differs from traditional technology in executing predefined procedures and also learning and identifying patterns that were not anticipated by their creators (Dattathrani & De', 2023).

In this context, the distinction between "digital work" and "non-digital work" is obsolete, according to Orlikowski and Scott (2016), because contemporary work practices are deeply entangled with digital technologies. Modern algorithms, which are more complex and less transparent, have reshaped the organization and valuation of work. This is evidenced by Karunakaran *et al.* (2022), who show how social media, with its visibility and unpredictability, forces organizations to adjust risks and service practices to meet new accountability demands. Thus, organizational reconfiguration involves both responses to external pressures and continuous adaptations in work practices, where human actions and digital technologies are intrinsically connected (Karunakaran *et al.*, 2022; Orlikowski & Scott, 2016).

3. Methodology

We followed a well-established approach to systematic reviews in the management field based on Tranfield *et al.* (2003), encompassing the planning and development of the research questions, the execution of the search and selection of studies, and the reporting of the findings, as well as the analysis and synthesis of the results to guide future research. To understand the state of the art regarding factors that facilitate and hinder AI adoption in auditing, we conducted a Systematic Literature Review (SLR) in the Web of Science and Scopus databases. We adopted the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, which comprises three phases: identification, screening, and eligibility, as illustrated in Figure 1. This approach is appropriate for exploring emerging questions and identifying future research opportunities (Webster & Watson, 2002).

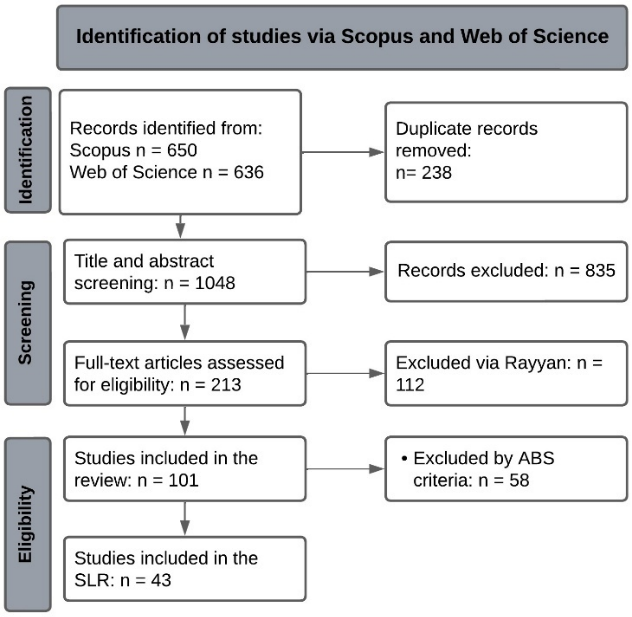

Figure 1. PRISMA Protocol

Legend: Description of the steps undertaken to obtain the sample.

In the identification phase, 1,286 studies were retrieved using the search string: (Topic: audit* AND Topic: “artificial intelligence” OR “natural language processing” OR “machine learning” OR “deep learning” OR “artificial neural network”) from the Scopus (n = 650) and Web of Science (n = 636) databases. Subsequently, duplicates were removed (n = 238), resulting in 1,048 unique records for screening.

In the screening stage, the titles and abstracts of the 1,048 articles were reviewed. As a result, 835 studies were excluded for not meeting the inclusion criteria (e.g., those addressing predominantly computational topics, the development of AI-based mathematical models unrelated to auditing practice, or the auditing of systems/information technology). At the end of the screening stage, 213 articles were selected for the next stage.

In the eligibility phase, these studies were assessed with the support of the Rayyan platform, which was used to organize the selection process and to record decisions and justifications. At this stage, 112 studies were excluded for not adhering to the scope and defined criteria after full-text review, resulting in 101 eligible studies to be included in the synthesis.

Finally, as a quality assessment stage, the ABS Academic Journal Guide (2024) was applied as a criterion to select journals with greater rigor and academic impact. Following this filtering process, 58 studies were excluded and 43 articles (listed in Appendix) were included in the SLR, enabling the identification of trends and the synthesis of evidence on the impacts of AI in auditing.

Although the sample comprises 43 articles, this number results from a rigorous selection process that maintains the consistency and relevance of the analyzed corpus. We follow prior studies in which the final sample size is obtained using similar techniques to synthesize evidence on emerging technologies and auditing. For example, Denter *et al.* (2023) conduct an SLR that, after successive screening stages, selects 52 articles for the final synthesis; Taylor *et al.* (2024) perform an SLR and retain 23 articles in the final sample. In addition, studies such as Wassie and Lakatos (2024), in their SLR with 16 articles, indicate that the use of AI in auditing is still in a consolidation phase and that empirical investigations remain limited. Therefore, our sample falls within the range of sizes commonly observed in comparable SLRs and is adequate to support a robust synthesis of the factors that drive and constrain the adoption of AI in auditing, as well as to identify research gaps.

For data analysis, an open-coding process was employed, organizing the data by meanings inferred by the researchers to assist in comparison and conceptualization (Boeije, 2010). Our specific focus was on the results and discussion sections, in which the studies made explicit the effects, whether benefits or challenges, of adopting AI in auditing. In each article, textual excerpts that expressed meanings relevant to the study were extracted, especially those related to factors that drive or inhibit AI adoption. These excerpts were organized in a spreadsheet to facilitate comparison across studies and the identification of convergences and divergences. The initial coding was conducted by one researcher, while the other researchers acted as validators, reviewing the extracted content and assessing whether the codes and resulting factors were consistent with the studies included in the sample. Because the coding was not conducted independently by multiple coders, no inter-rater reliability coefficient was computed. Instead, trustworthiness was pursued through iterative validation, discussion among the researchers, and consistency checks between the coding matrix and the studies included in the sample.

In the next stage, similar text excerpts were grouped to generate concepts that were later transformed into themes. These themes were then synthesized into analytical factors, classified as drivers or inhibitors according to the predominant meaning of the findings. For example, excerpts describing reduced audit time, automation of repetitive tasks, and expanded coverage were grouped under the factor "efficiency," classified as a driver of AI adoption. Coding was dynamic and data-driven, with codes developed from the data, initially identifying factors that support and inhibit the use of AI in auditing and subsequently revised, with some merged and others subdivided.

This methodological design also entails limitations. First, restricting the search to Web of Science and Scopus, followed by the application of the ABS Academic Journal Guide as a quality filter, may have privileged studies published in journals with stronger academic visibility and methodological rigor. However, this strategy may also over-represent narratives that frame AI as a transformative technology and under-represent evidence from unsuccessful adoption processes. Second, the temporal distribution of the final sample is concentrated mainly in the 2020–2024 period. As a result, the synthesis may partly reflect the recent AI hype cycle and the optimism surrounding emerging AI applications, rather than a balanced longitudinal view. These limitations should be considered when interpreting the identified drivers, inhibitors, and the resulting sociomaterial interpretation.

4. Results

This section presents the main findings, aiming to address our research questions and highlight the factors influencing AI adoption in auditing. The analyzed studies span from 1985 to 2024. Up to 2001, seven articles were identified, followed by a single article in 2012. From 2019 onward, there was a significant increase in publications, with 32 articles published between 2020 and 2024. Table 1 displays the primary factors identified.

Table 1. Main factors identified in the SLR

What factors drive the use of AI in auditing?	What factors hinder the use of AI in auditing?
Increased efficiency	Resistance to change
Accuracy/Quality	Algorithm aversion
Real-time/Continuous auditing	Heuristics and biases
Big Data analytics	Transparency/Explainability
Consistency and standardization	Expertise and training gaps
	Complexity

4.1 Discussion of drivers of AI use in auditing

4.1.1 Increased efficiency

The literature indicates that the expectation of efficiency gains resulting from the automation of routine tasks, thereby freeing time for more complex analyses, is one of the main drivers of AI adoption in auditing. These tools automate processes that do not require complex deliberation, enabling auditors to devote more time to higher-value activities (Samiolo *et al.*, 2024; Seethamraju & Hecimovic, 2023). Natural Language Processing (NLP) algorithms optimize the handling of large data volumes, significantly reducing the time needed for manual analyses (Wei *et al.*, 2023).

Faced with staffing shortages and cost pressures, AI emerges as a strategic solution. In the sense, based on the Technology–Organization–Environment (TOE) framework, Seethamraju and Hecimovic (2023) identified technological factors, organizational factors, and environmental factors that drive AI adoption, may increase audit efficiency and quality, especially when applied to structured tasks. The authors show that the technological factors associated with adoption include perceived benefits, which suggests that expected efficiency functions as a relevant motivator for the incorporation of these tools.

In this sense, the promise of greater efficiency encourages audit firms to invest in these tools. Commerford *et al.* (2022) highlight AI's ability to process diverse, unstructured data at scale, enhancing efficiency and effectiveness in complex tasks. In addition, algorithms and automation reduce the time spent on operational routines and expand the ability to engage in activities that require greater critical judgment (Tiron-Tudor & Deliu, 2022). Thus, AI adoption streamlines processes, enabling auditors to prioritize analytical and judgment-intensive activities.

The expected or delivered efficiency of AI goes beyond the automation of repetitive tasks. While the TOE framework identifies technological, organizational, and environmental conditions that favor AI adoption, the sociomaterial lens extends this view by showing how efficiency emerges from the reconfiguration of audit routines, professional judgment, and AI-enabled procedures. Its effectiveness depends on both technical capabilities (material agency) and the reconfiguration of auditors' practices to integrate these tools (social agency). AI therefore redefines auditors' work, demanding greater data-analysis expertise, algorithmic understanding, and result interpretation, thereby transforming the profession by enabling a focus on analytical and critical tasks.

4.1.2 Accuracy/Quality

Beyond boosting efficiency, AI implementation in auditing has been associated with improved quality of results. AI enables high-precision analysis of large data sets, reducing human error margins and increasing reliability (Aldemİr & Uçma Uysal, 2024). Goto (2023) studied AI adoption by the Big Four in Japan and reported significant improvements in service quality and productivity, with repetitive tasks automated and data analyzed more accurately and efficiently. Omoteso (2012) noted improvements in decision-making and communication, knowledge development for newcomers, and staff training quality, attributes that bolster audit quality.

AI also uncovers hidden patterns and provides more robust evidence, improving process quality (Mugwira, 2022). Detailed analyses build greater confidence in auditors' judgments. Samiolo *et al.* (2024), based on 44 interviews with auditors, regulators, and software vendors, emphasized AI's role in identifying anomalous transactions and risks, enhancing accuracy and reducing errors. As one interviewee observed:

> "*It's probably a good thing for the quality of audit because, obviously, if you're using your judgment to pick a sample, you'll pick the smallest sample you can. Whereas this will mandate proper coverage testing, even if we may not like it. So I think it's better for the quality of the audit.*" (Samiolo *et al.*, 2024, p. 584)

This perception is consistent with the literature, indicating that by replacing discretionary sample selection with broader and more systematic coverage, AI can enhance audit quality by increasing the extent of testing and reducing biases associated with human judgment. The study reinforces the idea that AI is seen as a means of expanding test coverage and reducing reliance on discretionary sampling, thereby increasing confidence in auditing (Samiolo *et al*., 2024). In this sense, quality functions as a driver when it is perceived as the promise of a more consistent audit and not merely as a technical outcome of the tool. In this context, Rahman and Ziru (2023) used fixed-effects regression models to examine client digitization and audit firms' digital expertise, including AI use. They found that more digitized firms have more efficient operating systems, reducing risks and improving audit quality. Additionally, Fedyk *et al.* (2022) concluded that both Big Four and non-Big Four firms investing in AI see enhanced analysis quality.

Accuracy and quality gains from AI depend on technical capabilities and on human–technology interaction. AI performativity, identifying hidden patterns, detecting anomalies, and reducing errors, is continuously shaped by auditors' practices and decisions. Thus, result quality reflects the entanglement of technology and auditors' capacity to integrate these tools.

4.1.3 Real-time/Continuous auditing

AI's application in auditing goes beyond efficiency and quality, enabling real-time information gathering and assessment (Han *et al.*, 2023; Ding, 2022; Fotoh & Lorentzon, 2021). Continuous auditing occurs regularly, replacing fixed cycles (e.g., annual or quarterly audits) and offering greater transparency, accuracy, and agility in organizational operations. Zhang *et al.* (2019) assert that AI facilitates continuous auditing by enabling frequent checks and real-time monitoring of client systems.

In this line of research, continuous auditing uses advanced technologies such as AI to automate risk analysis, exception identification, pattern detection, and trend reviews (Han *et al*., 2023). In addition, AI is seen as capable of facilitating continuous auditing capacity (Seethamraju & Hecimovic, 2023). The Big Four are investing in AI and blockchain to integrate continuous auditing into their practices, creating an ecosystem that enhances the process and provides more reliable assurance. According Han *et al*. (2023), continuous auditing will likely evolve toward a cohesive AI–blockchain ecosystem.

Supported by AI, continuous auditing meets the growing demand for rapid, accurate information (Fotoh & Lorentzon, 2021). Tiron-Tudor and Deliu (2022) emphasize that AI tools enable real time evidence collection and validation, as well as continuous monitoring, while Seethamraju and Hecimovic (2023) suggest that AI adoption can expand firms' capacity. Thus, AI performs tasks with greater speed and accuracy and also transforms organizational practices, influencing how auditors perceive, interpret, and respond to real time data.

In this way, as AI becomes central to the audit ecosystem, it shapes operations and interactions among auditors, clients, and stakeholders. This sociomaterial relationship requires constant renegotiation of practices and responsibilities, with AI providing rapid insights and auditors applying contextual judgment to add value.

4.1.4 Big data analytics

Modernizing auditing with tools that automate Big Data analysis addresses one of the sector's main challenges: processing vast data volumes (Lugli & Bertacchini, 2023; Almufadda & Almezeini, 2022; Singhvi *et al.*, 2021; Alles & Gray, 2020). Almufadda and Almezeini (2022) emphasize AI's ability to process and analyze data at scale, enabling more detailed and comprehensive audits that were previously impractical with traditional methods. This approach increases precision and efficiency, facilitating pattern, trend, and outlier identification (Singhvi *et al.*, 2021; Kend & Nguyen, 2020).

Interviews with Italian auditors by Lugli and Bertacchini (2023) show that the Big Four have greater capacity to invest in AI and Big Data Analytics (BDA), yielding more complete and accurate analyses. As one auditor noted: "*We used to analyse only samples, now we analyse everything! Analysing the whole lot gives an auditor security.*" This statement illustrates how the combination of AI and BDA shifts auditing from a sampling-based approach to one of broader transaction coverage, increasing the auditor's perceived assurance. In this sense, Kend and Nguyen (2020) indicate that BDA can expand auditing to analyses of entire populations rather than samples.

BDA is among the technologies that move auditors away from manual tasks, increasing the time available for more critical judgments (Kend & Nguyen, 2020).

In addition, automation also allows auditors to focus on analytical tasks while systems detect anomalies and patterns. Another interviewee explained:

> "*The software I use in my work is able to analyse all the transactions performed, by connecting to the company's ERP. Therefore, I can identify all the operations undertaken, for example, by a user profile which did not have the necessary authorizations, or all the transactions booked overnight, the transactions booked by users who have left the organization over time, transactions on public holidays, and transactions with anomalous amounts. The check is much more powerful and it only takes 3 clicks*." (Lugli and Bertacchini, 2023, p. 849)

By describing an automated verification in a few steps, the interviewee reinforces that BDA reduces the auditor's operational effort and frees up time for activities involving the interpretation and judgment of findings. Alles and Gray (2020) discuss how AI and Big Data are revolutionizing, highlighting automation and changes in the construction of trust. Traditionally based on auditors' competence, trust now also includes the accuracy and reliability of systems.

The integration of AI and Big Data in auditing represents a sociomaterial transformation, redefining auditor–data interactions. AI performativity accelerates and broadens data analysis, while also reshaping professional practices. Auditors can delegate pattern and anomaly indetification tasks to systems, focusing on higher-value activities that yield deeper, more robust analyses (Lugli & Bertacchini, 2023).

4.1.5 Consistency and standardization

Standardizing analyses is one of auditing's greatest challenges, essential for ensuring consistent results and avoiding disparities across engagements. AI contributes by eliminating human error and capturing implicit knowledge from large historical data sets, resulting in greater decision consistency (Roszkowska, 2021). AI also helps provide a "framework for audit tasks," contributing to work standardization (Omoteso, 2012). Instead of an ad-hoc approach, the system imposes a methodological sequence of steps and considerations. In addition, AI tools automate standardized tasks and can expand the operational consistency of audit procedures (Seethamraju & Hecimovic, 2023).

In this context, Wei *et al.* (2023) examined human and artificial cognition, analyzing how ChatGPT replicates financial auditors' cognitive schemas. The results suggest a better imitation of the cognitive patterns of more experienced auditors, especially when trained on well-structured data. ChatGPT's standardized outputs mirror experienced auditors' cognitive patterns, demonstrating its ability to reproduce consistent financial analyses and decisions.

Along the same lines, studies indicate that AI-based systems can reproduce more stable analysis patterns, especially when applied to well-structured data. In this way, automation can strengthen the uniformity of procedures and reduce dependence on dispersed manual interventions (Tiron-Tudor & Deliu, 2022). In this sense, Liao *et al.* (2024) observed that auditors trained in AI complete financial reports more quickly and automate structured tasks, while supporting complex activities. This improves efficiency and promotes consistency and standardization in audit processes. AI-based automated programs standardize data collection and analysis, making audits more reliable.

The integration of AI into the pursuit of consistency and standardization reveals a profound sociomaterial dynamic. By consolidating uniform analytical patterns, AI ensures more trustworthy results and reduces variability across audits. The interaction between auditors and AI systems underscores the interdependence of human practices and technological solutions, upholding consistency and raising quality standards.

4.2 Discussion of barriers to AI use in auditing

4.2.1 Resistance to change

Although AI brings significant benefits to auditing, there are barriers that can delay or compromise its full adoption. Resistance among auditors is one such barrier, often caused by the need to develop new skills, which generates discomfort and hesitation (Aldemİr & Uçma Uysal, 2024; Goto, 2023; Han *et al.*, 2023; Choi *et al.*, 2022; Ding, 2022; Tiron-Tudor & Deliu, 2022; Fotoh & Lorentzon, 2021; Roszkowska, 2021; Samiolo *et al.*, 2024; Shivram, 2024; Singhvi *et al.*, 2021; Zhang, 2019). According to Zhang (2019), this resistance reflects a natural conservatism when introducing technologies into traditional processes, especially in an area like auditing, which has historically valued human judgment and manual approaches.

In this context, Samiolo *et al.* (2024) identified auditors' concerns about overreliance on technology diminishing critical judgment and professional skepticism – fundamental elements of high-quality audits. One interviewee stated:

> "*It's really hard to teach auditing without some experience in auditing. It's just, when I was first starting, you look at something like a bank record and you say, I've got to pick a sample to look at. How do you know what to pick? And then people will go, oh, you just know. You know? The ones that look interesting. How? And then after a few years you just know*." (Samiolo *et al.*, 2024, p. 513)

This account underscores the concern over losing tacit knowledge gained through direct practice. Additional studies reinforce that resistance is exacerbated by auditing’s conservative nature and the fear that AI may devalue human expertise (Aldemİr & Uçma Uysal, 2024; Choi *et al.*, 2022). In addition, Choi *et al.* (2022) note that reluctance also stems from the complexity and unfamiliarity of the technology, as well as the perception that AI could supplant critical aspects of professional judgment.

From a sociomaterial perspective, this resistance reflects the impact of technological transformation on established practices and the meanings ascribed to work. Successful AI integration requires a dynamic balance between the materiality of the technology and auditors’ social practices, recognizing their mutual constitution. Resistance, therefore, can be seen as a phase of renegotiating sociomaterial arrangements, during which AI must be legitimized without devaluing human contributions.

4.2.2 Algorithm aversion

Resistance to change can lead to algorithm aversion, characterized by distrust in AI-generated recommendations even when they outperform human decisions (Commerford *et al.*, 2022). In one experiment, Estep *et al.* (2023) found that such aversion affects managers’ willingness to trust audit reports, leading to hesitation when recommendations originate from AI due to discomfort or mistrust.

This distrust arises because many believe that algorithms are ill-suited to handling subjective tasks (Liao *et al.*, 2024). The literature indicates that algorithm aversion may be linked to the perception that algorithmic information sources are inherently inferior to human sources (Commerford *et al*., 2022; Liao *et al*., 2024). This effect intensifies under uncertainty, such as when evaluating complex estimates.

In this context, Commerford *et al.* (2022), in a study of 170 auditors, concluded that auditors make smaller adjustments when evidence comes from AI compared to human sources. This heightened aversion in objective-data scenarios can compromise audit quality and stakeholder confidence in financial statements. In addition, Wei *et al.* (2023) show that ChatGPT can better reproduce the judgments of more experienced auditors, which suggests that acceptance of AI may increase when its results more closely resemble already recognized patterns.

This resistance reflects a sociomaterial tension in which those involved still value human agency, even in the face of AI’s superior accuracy. Algorithms, as material agents, challenge established beliefs and practices, demanding renegotiation of sociomaterial arrangements. Such an approach reconfigures sociomaterial practices in which social and material elements co-constitute one another continuously.

4.2.3 Heuristics and biases

As AI use in auditing increases, concern grows over the exacerbation of human heuristics and biases (Lombardi *et al.*, 2023; Munoko *et al.*, 2020). Almufadda & Almezeini (2022) warn of algorithmic bias – when input data reflect preexisting biases or patterns, causing algorithms to reinforce them. This problem worsens with low-quality or incomplete data, undermining decision reliability and leading to potentially misleading conclusions.

In a 50-year systematic review of audit biases, Lombardi *et al.* (2023) categorized biases according to Tversky and Kahneman's five heuristics: representativeness, availability, anchoring and adjustment, framing, and overconfidence. Although AI can improve audit quality, they identify "automation bias," where auditors overdepend on technological recommendations.

Moreover, AI opacity can aggravate biases by obscuring decision-making processes. This can lead to overconfidence in results or to anchoring bias, in which auditors rely too heavily on initial information provided by AI. In this context, the literature suggests that AI implementation should be accompanied by supervision, since AI training can help integrate these tools into professional judgment more effectively (Liao *et al.,* 2024; Tiron-Tudor & Deliu, 2022). Thus, careful AI implementation is essential to prevent biases from compromising audit quality (Lombardi *et al*., 2023).

In the same line, Choi *et al.* (2022) highlight that traditional AI models can introduce biases through modeling errors or omission of relevant variables. However, according to the authors, modern techniques such as deep learning and neural networks adjust parameters dynamically, mitigating these risks.

From a sociomaterial lens, the interplay between human heuristics and AI tools in auditing reflects the complexity of emerging practices. Bias amplification stems from individual limitations and from sociomaterial arrangements that shape auditor–algorithm relationships. Overcoming these challenges requires reflective and critical integration of technologies, ensuring material capabilities complement human skills for more balanced, robust decisions.

4.2.4 Transparency and explainability

Transparency and explainability are central to auditors' work and pose significant obstacles to AI adoption. Opaque AI models hinder auditors' ability to understand and justify decisions, compromising the documentation and evidence required to meet professional standards (Zhang *et al.*, 2022; Zhang, 2019).

According to Alles and Gray (2020), that the lack of explainability in AI models breeds distrust, since auditors must document how results were obtained and ensure the reliability of procedures used. In addition, the inability to adequately explain AI conclusions limits its utility in auditing, as auditors need to confirm that evidence is sufficient and appropriate (Zhang *et al*., 2022).

This challenge is illustrated by Samiolo *et al.* (2024), where an auditor reports:

> "*The bot comes back and says, 'Here are your material transactions that you need to test.' I'm not sure exactly how it works but the way that we use it, is there's a mailbox, we send it to a mailbox and then it comes back to us saying, 'Your bot has run and this is the output from the bot'.*" (Samiolo *et al.*, 2024, p. 513)

This account highlights the "black box" nature of many AI systems, where internal processes are unclear, hindering auditors' understanding. This black box perception can hinder adoption, which reinforces the importance of comprehensibility (Seethamraju & Hecimovic, 2023). To overcome this barrier, techniques that enhance AI transparency and interpretability, known as Explainable AI (XAI), have been proposed (Zhang *et al.*, 2022). The XAI makes AI models more interpretable, enabling auditors to understand and justify automated decisions, thereby strengthening trust in the technology, applying professional skepticism, and complying with regulations (Zhang *et al*., 2022).

From a sociomaterial perspective, explainability transcends a mere technical attribute of AI; it emerges from interactions among people, technologies, and organizational practices. Auditors' trust depends on algorithmic understanding and also on how the technology is integrated into processes, culture, and institutional norms. Sociomaterial explainability thus involves creating environments, protocols, and interfaces that foster shared comprehension, allowing auditors to robustly use AI while meeting regulatory demands and exercising professional skepticism.

4.2.5 Expertise and training

AI adoption in auditing demands new technological and analytical competencies, making expertise and training crucial factors (Samiolo *et al.*, 2024; Shivram, 2024; Singhvi *et al.*, 2021; Thottoli, 2024; Huang & Wang, 2023; Kend & Nguyen, 2020; Lugli & Bertacchini, 2023; Rahman & Ziru, 2023; Zhang *et al.*, 2022). In the sense, Singhvi *et al.* (2021) emphasize ongoing investment in education and training to keep auditors abreast of rapid technological changes. Zhang *et al.* (2022) point out that lack of technical knowledge is a major obstacle, undermining AI adoption, while Rahman and Ziru (2023) highlight that limited data-analysis skills reduce these tools' effectiveness.

In this context, comparing Big Four and non-Big Four auditors, Lugli and Bertacchini (2023) show that large firms have greater capacity to invest in technology, but effective use requires advanced technical knowledge. One interviewee stated: "*Technological knowledge will be needed to understand how tools work: not just the tools auditors use, but those used by companies as well*". The statement suggests that, without a conceptual understanding of the tools and systems analyzed, adoption tends to be superficial, limiting the ability to interpret results and perform professional judgment.

Another interviewee described the transformation underway:

> "*Our unit has grown not only in terms of staff numbers but also with regard to its spectrum of competencies, because after seventy years of auditing in more or less the same way, we are now experiencing a minor revolution in the auditing industrial process. A technological auditor or an accounting technician will be required. Accounting skills alone will no longer suffice.*" (Lugli & Bertacchini, 2023, p. 850)

This account reinforces that the adoption of AI is not merely incremental but entails a shift in the professional profile, with an expansion of the skill set and the emergence of a hybrid role between auditing and technology. Lack of technical expertise, especially among practitioners with traditional backgrounds, poses a significant barrier to widespread AI adoption (Singhvi *et al.*, 2021). In this sense, Huang and Wang (2023) suggest incorporating machine learning into auditing and accounting curricula, with hands-on exercises – such as building predictive models in real scenarios – to prepare future auditors for a technology-driven market.

This skills gap reflects a misalignment in sociomaterial arrangements, where AI's advanced materiality has yet to be matched by the social capabilities needed for full utilization. To reconfigure these practices, continuous training is essential, integrating technical learning into auditors' daily routines. Such technological upskilling facilitates AI adoption and strengthens the sociomaterial practices that underpin audit quality and efficiency.

4.2.6 Complexity

The inherent complexity of AI systems is a critical factor contributing to auditors' skills gap. Effective AI adoption and implementation depend on users' deep understanding, and high complexity can hinder widespread application (Goto, 2023; Ding, 2022; Zhang *et al.*, 2022). According to Choi *et al.* (2022), technologies such as neural networks require vast training data, data-science expertise, and advanced computing infrastructure, representing significant obstacles for many audit firms.

The "black box" created by algorithmic complexity, due to opaque internal processes, can compromise transparency and explainability (Thottoli, 2024;

Lombardi *et al.*, 2023). This opacity can trigger "automation bias," where auditors overtrust automated decisions without critical review. In auditing, such reliance is a serious risk, as opaque decisions may undermine process confidence and accuracy (Lombardi *et al.*, 2023).

Moreover, complexity is not limited to the tool itself but extends to the way auditors incorporate system-generated evidence in contexts of uncertainty (Commerford *et al.*, 2022). In this sense, Thottoli (2024) highlights that complexity is further aggravated by the need for specialized information-systems knowledge, essential for auditors to plan and review AI-assisted work. In addition, transferring knowledge-management strategies into auditing practices faces challenges in tech-driven environments, where regulations and IT expertise gaps further impede AI adoption.

From a sociomaterial viewpoint, AI system opacity underscores the need to translate technological complexity into accessible, comprehensible practices for auditors. Automation bias reflects an imbalance in sociomaterial arrangements, where human agency is weakened in favor of technological materiality. Overcoming these challenges requires reconfiguring organizational practices that align technological complexity with social demands, creating more balanced and effective sociomaterial arrangements.

4.3 The sociomaterial relationship of AI and auditing

AI adoption in auditing is influenced by various factors that affect its implementation and use within organizational practices, as discussed above. Below, we highlight how these factors impact AI uptake and also drive (or constrain) a profound transformation in how auditors perform their roles, redefining competencies, responsibilities, and decision-making processes. While the previous sections are dedicated to identifying the main drivers and inhibitors of AI adoption in auditing, this section develops a theoretical synthesis generated by applying the sociomaterial lens to those findings. The propositions below should therefore be read as interpretive claims about how the identified factors reconfigure audit work through the interaction among AI systems and auditors' practices.

4.3.1 Drivers and the reconfiguration of the auditor's role

Sociomateriality theory offers a comprehensive view of the AI–auditing nexus, showing that technology both shapes and is shaped by auditors' practices. In the sense, Orlikowski and Scott (2008) argue that the social and the material co-constitute each other, so as auditors interact with AI, their practices and behaviors are transformed. From Leonardi *et al.*'s (2012) standpoint, effective AI use involves an imbrication between technology and auditors' practices, in which both adapt in tandem. In this sense, AI facilitates work and redefines the quality criteria deemed essential in auditing. This interdependence generates new opportunities for practice, bolstering confidence in outcomes.

The efficiency gains provided by AI illustrate how automating repetitive tasks and processing large data volumes (Samiolo *et al.*, 2024; Seethamraju & Hecimovic, 2023; Wei *et al.*, 2023) depend on AI's technical capabilities (material agency) and on how auditors adjust their practices to integrate these technologies (social agency). AI's materiality directly influences auditors' work, leading them to prioritize more analytical and critical tasks (Commerford *et al.*, 2022), thereby elevating the value of their activities. Under a sociomaterial lens, AI (as an artificial agent) does not operate in isolation but in concert with auditors' agency, resulting in a dynamic process of mutual influence. This differs from a TOE-based interpretation, which would situate efficiency and quality within perceived benefits and related technological adoption conditions (Seethamraju & Hecimovic, 2023). From a sociomaterial perspective, these factors become outcomes of how AI-enabled procedures are incorporated into the audit process. This interpretation is consistent with Salijeni *et al.* (2021), who show that BDA tools reconfigure financial statement audits reshaping relational dynamics within audit firms.

Proposition: The implementation of AI in auditing is driven by factors that promote interdependence between technology and auditors' social practices.

This imbrication becomes clear as the AI–auditor relationship intensifies. However, its depth varies according to the audit client's characteristics. In clients with low digital maturity, material limitations curb effective AI use, requiring greater human intervention to adapt processes. In highly digitized environments, interdependence is deeper. Auditing's goal, producing high-quality reports to support decision-making, relies on attributes such as consistency, standardization, and accuracy. In this context, auditors deploy their social agency to shape AI performativity, creating sociomaterial outcomes in which both technology and professionals transform one another.

Simultaneously, artificial agency capabilities reconfigure organizational practices, creating opportunities for auditors to focus on higher-value, more complex analyses. Yet, realizing this opportunity depends on how efficiency gains are managed. Under constant pressure to cut costs and time, there is a risk that hours freed by automation will be trimmed rather than reinvested in improving audit quality. Conversely, AI tools evolve through auditor feedback, while auditors continuously reassess practices and processes in light of new technological functionalities. Thus, AI's impact on auditing is dynamic. New interactions between social and artificial agents emerge as AI use becomes more frequent and sophisticated, generating continuous cycles of transformation. Therefore, the auditor's role is evolving as AI can support professional practices, but the responsibility for judgment, skepticism, and the audit opinion remains with the auditor.

Proposition: AI adoption reconfigures auditors toward a more analytical role, while independence requirements keep audit judgment anchored in professional responsibility.

4.3.2 Inhibitors and the reconfiguration of the auditor's role

While sociomateriality highlights the benefits of AI–auditor imbrication, significant barriers hamper this integration. The inhibitors identified in the SLR, intrinsic to AI technologies, illustrate the challenges of embedding new technologies into established social practices. As discussed, this relationship evolves over time through interactions among stakeholders, reconfiguring both auditing practices and AI itself as adjustments are made.

From a sociomaterial interdependence perspective, barriers to AI use lead to underutilization of these technologies. Lack of technical knowledge restricts auditors' ability to fully exploit AI performativity, limiting practice changes that AI could drive. Moreover, these barriers are not merely human issues but reflect an incomplete social, material relationship. For example, algorithm aversion is not interpreted here solely as a psychological reluctance to rely on AI, but as an incomplete sociomaterial imbrication in which algorithmic outputs have not yet been sufficiently integrated into audit practices and routines. Even with available technology, auditors' lack of adaptation prevents full development of this interaction, resulting in suboptimal organizational practice reconfiguration. Thus, despite AI's presence, its impact remains limited, and audits continue under traditional methods. This technological resistance impedes mutual constitution between the social and the material, constraining AI's transformative potential.

Proposition: Barriers to AI adoption in auditing delay changes in auditors' functions, hindering reconfiguration toward a more analytical role.

A clear example of sociomaterial interaction is algorithmic bias. Sophisticated machine-learning tools embed patterns in their predictions and decisions, potentially amplifying preexisting biases (Almufadda & Almezeini, 2022). These biases are not merely technical (material) but also deeply social, emerging from how AI is developed and trained. Since artificial agents are partly shaped by human and material perceptions (van Rijmenam & Logue, 2021), AI biases reflect the interplay between human biases and AI's capacity to absorb them. Therefore, effective AI use challenges are rooted in integrating artificial agency into established social practices.

In this context, Leonardi (2013) introduces critical realism, proposing that sociomaterial relations become interdependent and evolve over time. From this view, auditors' agency can refine artificial agency through continual practice. However, the reverse also holds: barriers, like those impeding AI use, stifle this interaction's evolution. These obstacles are not external but intrinsic to the sociomaterial process, arising within organizational practices. Overcoming them is essential to enhance AI tools' effectiveness in auditing. This is particularly relevant in auditing because the acceptability of AI-enabled procedures is determined whether their outputs can satisfy professional and regulatory expectations for evidence (Seethamraju & Hecimovic, 2023).

Proposition: Inhibiting factors to AI integration in auditing are partly driven by regulatory standards, as automation reaches institutional limits when algorithmic results cannot be sufficiently reliable, explainable, and auditable to serve as evidence supporting the auditor's opinion.

4.4 Research contributions and directions for future research

Table 2 synthesizes the main recent review studies on the integration of AI technologies in auditing, showing how the literature has advanced across different, and to some extent complementary, fronts: the mapping of AI applications and impacts throughout the audit workflow; the categorization of benefits, challenges, and barriers; and discussions on trust infrastructures and verifiable data that can support more automated and continuous auditing.

Table 2. Related studies

Study	Objective	Main Findings	Contribution
De Jesus Silva Dos Santos & Dos Santos (2025) Technological convergence in financial auditing	To consolidate the contributions of AI, blockchain, ML, and DL to financial auditing and identify research gaps	Technologies expand big data analysis, improve quality and credibility, and mitigate fraud; costs, cyber risks, and skill gaps limit adoption	Broad mapping across four technologies and a research agenda (including gaps related to independence and governance)
Anwar & Akeel (2026) Integrating AI in audit workflow	To map AI applications across audit workflow stages, assess effects on effectiveness, efficiency, and quality, and identify barriers; to propose a reference architecture	ML/NLP/RPA already support planning, testing, and reporting; gains in coverage and efficiency; barriers related to data, explainability, skills, and regulation	Phase-based taxonomy and layered architecture with human-in-the-loop and governance

Study	Objective	Main Findings	Contribution
Kassar & Jizi (2026) AI & RPA in auditing and accounting	To identify benefits, challenges, drivers, and endorsement of AI and RPA in auditing and accounting	Benefits: monetary, quality, operational, and client-related; challenges: ethical, regulatory, social, and technical; initial resistance driven by trust and employment concerns	Categorization framework for benefits and challenges, and discussion of endorsement versus resistance
Suyono *et al.* (2025) AI in Auditing: tools, applications, challenges	To examine AI tools, applications in internal and financial auditing, and implementation challenges	Increasing use of ML/NLP/RPA for fraud detection, risk assessment, testing, and compliance; challenges related to privacy, ethics, skills, and regulatory uncertainty	Recent overview emphasizing tools and research gaps (need for standardized frameworks)
Han *et al.* (2023) Blockchain & AI in accounting/auditing	To analyze how blockchain improves transparency and trust, and how validated data support AI-enabled auditing	Four themes: event approach, real-time accounting, triple-entry accounting, and continuous auditing; highlights concerns (privacy, scalability, standards, governance)	Integrates blockchain as a source of "trusted data" for AI and discusses implications for Big Four firms versus small and medium practices (SMPs)

In that regard, although these studies provide valuable overviews, the specific contribution of the present study lies in integrating the mapping of drivers and inhibitors of AI adoption with a theoretical explanation grounded in sociomateriality, demonstrating that AI does not function merely as an automation tool but as an element that continuously reconfigures the auditor's role (competencies, judgments, routines, and responsibilities) through the interdependence between social, material, and artificial agency.

Moreover, by showing that both benefits and barriers may emerge from sociomaterial arrangements under constant negotiation, our study contributes to advancing a perspective that moves beyond an instrumental view of technology toward a broader understanding of the transformation of auditing work, offering an analytical foundation to inform management and governance decisions.

Based on this analysis and the identification of the main factors that drive and inhibit the use of AI in auditing, we outline several promising directions for future research. Table 3 presents research questions developed based on the suggestions from the analyzed studies, adapted to the central theme of this work and enriched with original insights derived from the literature review, with an emphasis on the interaction between AI and auditing.

Table 3. Research agenda

Theme/Factor	Guiding research question
Increased Efficiency	What are the costs and benefits of adopting Explainable AI (XAI), considering implementation expenses and potential gains in transparency and documentation? Which audit phases are most impacted by these technologies, and how can auditors integrate them into decision making?
Accuracy/Quality	How can XAI improve auditors' ability to interpret machine-learning outcomes and enhance audit quality? What types of AI-focused auditor training can impact efficiency, accuracy, and quality in auditing? How does AI integration in auditing affect users' perceptions of audit quality and cost?
Real-Time/Continuous auditing	How will blockchain technology paired with AI change the continuous auditing process, and what knowledge must auditors acquire to use these technologies? Does AI-enabled continuous auditing maximize service value? If so, in what ways?
Consistency and standardization	What standards should be established to facilitate AI adoption in auditing? How might this benefit auditing in the long term?
Big data analytics	How can emerging technologies – AI, blockchain, and Big Data Analytics (BDA) – create greater segregation between Big Four firms and mid-tier audit firms?
Algorithm aversion	How do different AI system characteristics and capabilities affect auditors' trust and mitigate algorithm aversion? Which interventions effectively reduce this aversion, and how can auditors become more willing to rely on AI?
Resistance to change	How is a growth mindset essential for new auditors adapting to rapid technological change? How does organizational culture influence AI adoption? Are innovation-focused firms more open to AI use?
Heuristics and biases	What uninvestigated biases – such as conjunction fallacy, base-rate fallacy, and sunk-cost effect – exist in the audit-AI literature, and can emerging technologies mitigate them? How can AI mitigate common biases in auditing?
Transparency and explainability	How does algorithmic process transparency influence auditors' trust in and reliance on AI tools?

Theme/Factor	Guiding research question
Expertise and training	How might BDA and AI adoption alter auditors’ skill sets and professional identities? What curriculum gaps exist? How can technical skills – data analysis and visualization – be incorporated into undergraduate and continuing professional education for auditors? What are the impacts of AI on entry barriers and the obsolescence of certain auditor skills?
Complexity	How comprehensible are interpretations provided by XAI techniques to auditors? In what ways can XAI-based tools be made reliable for auditing?

Legend: Suggestions for future research related to factors impacting AI tool use in auditing, inspired by articles in the sample.

These questions aim to guide new investigations, encouraging exploration of under-researched aspects and advancing knowledge on AI application in auditing.

5. Conclusion

This study explored the factors that facilitate and hinder AI adoption in auditing from a sociomateriality perspective, revealing how technology and auditors’ practices interweave and transform one another. By analyzing drivers and inhibitors of AI use, we identified tangible benefits in terms of efficiency and accuracy and the complex challenges arising from interactions between human and artificial agents.

The sociomaterial lens broadened our view of AI beyond a mere tool, recognizing it as an active agent that redefines auditors’ roles and audit practices. AI automates routine tasks and demands that auditors develop new analytical and strategic competencies, shaping the future of human-machine collaboration.

However, AI integration in auditing is not without obstacles. We observed barriers to fully realizing AI’s potential, including resistance to change, algorithm aversion, technological complexity, biases, lack of transparency and explainability, and auditors’ technical skills gaps. These inhibitors underscore the need for a holistic approach to overcome challenges.

From a sociomaterial standpoint, AI adoption in auditing depends on the mutual shaping of technology and professional practices. AI optimizes auditors’ activities and reconfigures their work, enabling greater focus on high-value tasks amid continuous adaptation as technology evolves. Yet, inhibiting factors constrain this full integration. The sociomaterial lens thus reveals that auditor reconfiguration occurs dynamically and continuously, hinging on both technological capabilities (artificial agency) and professionals’ engagement and adaptation (social agency).

The future research directions outlined here aim to deepen and integrate inquiry in this field, extending the perspective on AI beyond its role as a tool. By probing issues such as AI's influence on decision-making and the need for regulation, we contribute to an informed, constructive debate on auditing's future in the AI era.

Ultimately, this study highlights the importance of viewing AI not merely as technology but as a sociomaterial phenomenon reshaping auditing in profound, lasting ways. By acknowledging the interdependence of audit professionals and AI, we can chart a path that maximizes AI's benefits, mitigates its risks, and promotes an audit practice that is more efficient, reliable, and ethical.

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Appendix: Sample of SLR

Title	Journal	Authorship
A comparison of machine learning techniques with a qualitative response model for auditor's going concern reporting	Expert Systems with Applications	Anandarajan and Anandarajan (1999)
Accounting and auditing with blockchain technology and artificial Intelligence: A literature review	International Journal of Accounting Information Systems	Han *et al.* (2023)
Adoption of artificial intelligence in auditing: An exploratory study	Australian Journal of Management	Seethamraju and Hecimovic (2023)

Title	Journal	Authorship
AI competencies for internal auditors in the public sector	EDPACS	Aldemîr and Uçma Uysal (2024)
An experimental investigation of the effects of artificial intelligence systems on the training of novice auditors	Managerial Auditing Journal	Wongpinunwatana *et al.* (2000)
Anticipatory innovation of professional services: The case of auditing and artificial intelligence	Research Policy	Goto (2023)
Application of artificial-intelligence to accounting, tax, and audit services - research at Brigham-Young-University	Expert Systems with Applications	Meservy *et al.* (1992)
Applying Deep Learning to Audit Procedures: An Illustrative Framework	Accounting Horizons	Sun (2019)
Applying robotic process automation (RPA) in auditing: A framework	International Journal of Accounting Information Systems	Huang and Vasarhelyi (2019)
Artificial Intelligence Applications in the Auditing Profession: A Literature Review	Journal of Emerging Technologies in Accounting	Almufadda and Almezeini (2022)
Artificial neural network models for predicting patterns in auditing monthly balances	Journal of the Operational Research Society	Koskivaara (2000)
Artificial-intelligence and generalized qualitative-response models - an empirical-test on 2 audit decision-making domains	Decision Sciences	Hansen *et al.* (1992)
Audit Digitalization and Its Consequences on the Audit Expectation Gap: A Critical Perspective	Accounting Horizons	Fotoh & Lorentzon (2023)
Audit quality and digitalization: some insights from the Italian context	Meditari Accountancy Research	Lugli and Bertacchini (2023)
Auditing with ai: a theoretical framework for applying machine learning across the internal audit lifecycle	EDPACS	Shivram (2024)
Auditor Judgment Bias Research: A 50-Year Trend Analysis and Emerging Technology Use	Journal of Information Systems	Lombardi *et al.* (2023)
Auditor judgment in the fourth industrial revolution	Contemporary Accounting Research	Samiolo *et al.* (2024)
Auditor: a microcomputer-based expert system to support auditors in the field	Expert Systems with Applications	Dungan and Chandlers (1985)
Big Data Analytics and Other Emerging Technologies: The Impact on the Australian Audit and Assurance Profession	Australian Accounting Review	Kend and Nguyen, (2020)

Title	Journal	Authorship
Clients' digitalization, audit firms' digital expertise, and audit quality: evidence from China	International Journal of Accounting and Information Management	Rahman and Ziru (2023)
Development of an Intelligent NLP-Based Audit Plan Knowledge Discovery System	Journal of Emerging Technologies in Accounting	Li and Liu (2020)
Drivers of and barriers to decision support technology use by financial report auditors	Decision Support Systems	Meredith *et al.* (2020)
Enterprise Intelligent Audit Model by Using Deep Learning Approach	Computational Economics	Ding (2022)
Explainable Artificial Intelligence (XAI) in auditing	International Journal of Accounting Information Systems	Zhang *et al.* (2022)
Exploring the deep neural network model's potential to estimate abnormal audit fees	Management Decision	Choi *et al.* (2022)
Fintech in financial reporting and audit for fraud prevention and safeguarding equity investments	Journal of Accounting and Organizational Change	Roszkowska (2021)
How do financial executives respond to the use of artificial intelligence in financial reporting and auditing?	Review of Accounting Studies	Estep *et al.* (2023)
Hyperbole or reality? The effect of auditors' AI education on audit report timeliness	International Review of Financial Analysis	Liao *et al.* (2024)
Intelligent Process Automation in Audit	Journal of Emerging Technologies in Accounting	Zhang (2019)
Internet Related Technologies in the auditing profession: A WOS bibliometric review of the past three decades and conceptual structure mapping	Revista de Contabilidad-Spanish Accounting Review	Mugwira (2022)
Introducing Machine Learning in Auditing Courses	Journal of Emerging Technologies in Accounting	Huang and Wang, (2023)
Is artificial intelligence improving the audit process?	Review af Accounting Studies	Fedyk *et al.* (2022)
Is ChatGPT competent? Heterogeneity in the cognitive schemas of financial auditors and robots	International Review of Economics and Finance	Wei *et al.* (2023)

Title	Journal	Authorship
Leveraging information communication technology (ICT) and artificial intelligence (AI) to enhance auditing practices	Accounting Research Journal	Thottoli (2024)
Man Versus Machine: Complex Estimates and Auditor Reliance on Artificial Intelligence	Journal of Accounting Research	Commerford *et al.* (2022)
New auditors are coming: disrupting the fixed mindset and exploring dynamic changes in auditing	EDPACS	Singhvi *et al.* (2021)
Reflections on the human-algorithm complex duality perspectives in the auditing process	Qualitative Research in Accounting and Management	Tiron-Tudor and Deliu (2022)
Report Users' Perceived Sentiments of Key Audit Matters and Firm Performance: Evidence from a Deep Learning-Based Natural Language Processing Approach	Journal of Information Systems	Liu *et al.* (2022)
The application of artificial intelligence in auditing: Looking back to the future	Expert Systems with Applications	Omoteso (2012)
The Ethical Implications of Using Artificial Intelligence in Auditing	Journal of Business Ethics	Munoko *et al.* (2020)
The Impact of Digitalization on Future Audits	Journal of Emerging Technologies in Accounting	Fotoh and Lorentzon, (2021)
Transferring auditors' internal control evaluation knowledge to management	Expert Systems with Applications	Changchit *et al.* (2001)
Will the Medium Become the Message? A Framework for Understanding the Coming Automation of the Audit Process	Journal of Information Systems	Alles and Gray (2020)