Vaasan yliopisto
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The impact of artificial intelligence on the role of auditors in international audit firms

School of Management
Master's thesis in International Business

Vaasa 2025

UNIVERSITY OF VAASA	
School of Management	
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Title of the Thesis:	The impact of artificial intelligence on the role of auditors in international audit firms
Degree:	Master of Science in Economics and Business Administration
Programme:	International Business
Supervisor:	William Degbey
Year:	2025 **Pages:** 103

ABSTRACT:
Artificial intelligence (AI) has revolutionised many industries and is expected to transform auditing as well. Technological advancements have raised questions on whether AI will replace auditors with automation or assist auditors by augmenting their capabilities. This study aims to fill a current research gap by exploring how AI automation and augmentation will affect the role of auditors in international auditing companies by examining the benefits and challenges of AI automation and augmentation for international auditing firms.

The research was conducted as a qualitative study. The data was collected through semi-structured interviews and analysed thematically. The sample consists of nine executives from international auditing companies based in Finland. The findings were analysed through the study's theoretical framework, which consists of the automation-augmentation paradox, the concept of human-AI coexistence, and the co-piloted auditing model.

The findings suggest that AI will not replace auditors but will support their work and augment their capabilities. As a result, the auditor's role and responsibilities are expected to transform. As AI automates routine tasks, auditors' focus is expected to shift towards more analytical tasks. Changes in team structure are also expected as AI is integrated into audit teams. This creates hybrid teams that consist of humans and machines, supporting the idea of human-AI coexistence. This shift in the auditor's role highlights the need for auditors to acquire new skills and develop old ones to succeed in an AI-driven environment.

This study also presents the main benefits and challenges AI can bring to international audit companies. The findings suggest that AI can bring audit companies many benefits, including increased efficiency, enhanced quality, improved work experience, and risk detection. From these benefits, increased quality, efficiency and work experience can be considered automation-driven, while improved risk detection can be considered more related to augmentation. The findings also indicate that AI can present several challenges for audit companies. Challenges, such as a lack of trust and transparency, as well as regulatory uncertainty, can relate to either automation or augmentation, while overreliance and data standardisation can be considered more connected to automation.

The findings of this study indicate the need to adapt to the upcoming changes in auditors' roles by ensuring auditors have the necessary skills to work alongside AI systems efficiently. This calls for AI training in auditing firms and a willingness to learn new technologies from auditors. Another recommendation is that organisations should encourage and improve human-AI collaboration to fully reap the benefits of AI use. Finally, regulators should provide clear instructions on responsible AI use.

KEYWORDS: auditing, auditors, international audit firms, artificial intelligence, automation, augmentation, coexistence

VAASAN YLIOPISTO
Johtamisen akateeminen yksikkö
Tekijä: Kia Kotivirta
Tutkielman nimi: The impact of artificial intelligence on the role of auditors in international audit firms
Tutkinto: Kauppatieteiden maisteri
Oppiaine: International Business
Työn ohjaaja: William Degbey
Valmistumisvuosi: 2025 **Sivumäärä:** 103

TIIVISTELMÄ:

Tekoäly on mullistanut lukuisia toimialoja, ja sen odotetaan tuovan muutoksia myös tilintarkastukseen. Teknologian jatkuva kehitys on herättänyt kysymyksiä siitä, tuleeko tekoäly korvaamaan tilintarkastajat automaation avulla vai avustamaan tilintarkastajia täydentämällä heidän ominaisuuksiaan. Tämä tutkimus pyrkii vastaamaan olemassa olevaan tutkimusaukkoon tutkimalla tekoälyautomaation ja -augmentaation vaikutuksia tilintarkastajan rooliin kansainvälisissä tilintarkastusyrityksissä tarkastelemalla tekoälyautomaation ja -augmentaation tuomia hyötyjä ja haittoja kansainvälisille tilintarkastusyrityksille.

Tutkimus toteutettiin laadullisena tutkimuksena. Sen aineisto kerättiin puolistrukturoiduilla haastatteluilla sekä analysoitiin ja esiteltiin temaattisesti. Otos koostuu yhdeksästä eri haastateltavasta Suomessa toimivista kansainvälisistä tilintarkastusyrityksistä. Tuloksia tarkasteltiin tutkimuksen teoreettisen viitekehyksen kautta, joka koostuu automaatio-augmentaatio paradoksista, ihmisen ja tekoälyn rinnakkaiselon käsitteestä (human-AI coexistence) sekä yhteisohjatun tilintarkastuksen mallista (co-piloted auditing).

Tutkimustulokset esittävät, että tekoäly ei tule korvaamaan tilintarkastajia vaan se tulee tukemaan heidän työtään sekä täydentämään heidän osaamistaan. Tämän seurauksena tilintarkastajan roolin ja vastuualueiden odotetaan muuttuvan. Tekoälyn automatisoidessa rutiinitehtäviä tilintarkastajien työ tulee keskittymään enemmän analyyttisiin tehtäviin. Tekoälyn integroiminen tilintarkastustiimeihin muuttaa tiimien rakennetta luoden hybriditiimejä, jotka koostuvat ihmistilintarkastajista sekä koneista. Nämä muutokset korostavat tilintarkastajien tarvetta hankkia uusia taitoja sekä kehittää vanhoja menestyäkseen tekoälyn muovaamassa työympäristössä.

Tutkimustulosten mukaan tekoäly voi hyödyttää tilintarkastusyrityksiä parantamalla tehokkuutta ja laatua, lisäämällä työn mielekkyyttä sekä parantamalla riskien tunnistusta. Näistä hyödyistä parantunut tehokkuus ja laatu sekä työn mielekkyys liitettiin automaatioon, kun taas riskien tunnistus kytkeytyy enemmän augmentaatioon. Tutkimus tunnisti myös tekoälyyn liittyviä haasteita, kuten luottamuksen ja läpinäkyvyyden puutteen sekä sääntelyn epävarmuuden, jotka voivat liittyä sekä automaatioon että augmentaatioon. Automaatioon yhdistettyjä haasteita olivat liiallinen tekoälyyn tukeutuminen sekä tarve datan standardoinnille.

Tutkimustulokset viittaavat siihen, että tilintarkastajien roolin muutokseen on syytä varautua varmistamalla, että tilintarkastajilla on tarvittavat taidot työskennellä tehokkaasti tekoälyn rinnalla. Tämä edellyttää tilintarkastusyrityksiltä tekoälykolutusta ja tilintarkastajalta halukkuutta oppia uusia teknologioita. Yritysten tulisi tukea tilintarkastajien ja tekoälyn välistä yhteistyötä, jotta tekoälyn tuomia hyötyjä voidaan hyödyntää käytännössä. Säätelevien elinten tulisi myös asettaa selkeät ohjeet tekoälyn vastuulliselle käytölle tilintarkastuksessa.

AVAINSANAT: auditing, auditors, international audit firms, artificial intelligence, automation, augmentation, coexistence

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Abbreviations

AI = Artificial intelligence

GAAP = Generally Accepted Accounting Principles

GenAI = Generative AI

IAASB = International Auditing and Assurance Standards Board

IESBA = International Ethics Standards Board for Accountants

IFRS = International Financial Reporting Standards

ISA = International Standards on Auditing

ML = Machine learning

NLP = Natural language processing

OCR = Optical character recognition

RPA = Robotic process automation

PRH = Finnish Patent and Registration Office

1 Introduction

In this part, the thesis is introduced by first explaining the background of the study, then presenting the research questions and aims, and finally presenting and defining the main concepts and providing the structure of the study.

1.1 Background of the study

Artificial intelligence (AI) is currently transforming businesses across all sectors (Holmström & Carroll, 2024). The use of AI has increased significantly during the last decade, as AI adoption in organisations' business functions has increased from 20% in 2017 to 78% in 2024 (McKinsey & Company, 2024). AI has also received attention in research, as studies using the keywords "AI" or "artificial intelligence" have nearly doubled in Scopus, from approximately 40 thousand in 2022 to 79 thousand in 2024 (Scopus, 2025). More recently, the introduction of generative AI, the technology behind commonly known applications such as ChatGPT, has received further attention due to its disruptive potential for society and organisations (Holmström & Carroll, 2024).

The rapid implementation of AI technologies into businesses has sparked debate on AI's effects on jobs. AI is expected to impact employment within all fields (Huang et al., 2019) but the question remains whether AI will replace human workers or augment human intelligence by enhancing their capabilities (Raisch & Krakowski, 2021). Some see AI as a threat to human employment, fearing it will take over jobs, while others believe AI will enhance human abilities and generate new job opportunities (Huang et al., 2019; Szczepański, 2019).

Auditing is one of the professions likely to be transformed by artificial intelligence (Seethamraju & Hecimovic, 2023). While non-AI technologies such as robotic process automation (RPA) and data analytics have already been widely implemented in auditing (Töngi, 2023), the implementation of artificial intelligence, especially generative AI, is expected to bring significant changes to the audit profession (Anica-Popa et al., 2024;

Rikhardsson et al., 2022; Rodrigues et al., 2023; Zhang et al., 2020). Consequently, significant shifts in auditors' responsibilities are expected within the next decade (Hasan, 2022). While it is unclear how the future of the audit profession will look (Rodrigues et al., 2023), previous studies have identified some anticipated changes to the auditor's role. The auditor's role is expected to include AI supervision (Kokina et al., 2025), and auditors' focus will likely shift from manual tasks towards more important areas (Fedyk et al., 2022). In addition to the expected changes to the auditor's role, the implementation of AI in auditing raises questions about the future role of human auditors and the possibility of job displacement due to automation (Du, 2024). While Frey and Osborne (2017), have presented that there is a 94% chance that auditing and accounting jobs will be automated, many recent studies agree that AI will not replace auditors (Law & Shen, 2024; Vitali & Giuliani, 2024).

Audit firms are investing billions of dollars in developing AI systems that can assist in auditing (Commerford et al., 2021). The expected benefits from AI use include improved efficiency, quality, risk management and decision-making (Abdullah & Almaqtari, 2024; Fedyk et al., 2022; Vitali & Giuliani, 2024). Despite the transformative potential of AI, its application in auditing firms is still in its early stages (Kokina et al., 2025). Barriers such as a lack of transparency (Seethamraju & Hecimovic, 2023) and regulatory uncertainty (Kokina et al., 2025), can limit AI adoption. There are also some challenges that auditing firms can face when using AI, such as bias, data security risks, deskilling, over- and underreliance (Kokina et al., 2025; Munoko et al., 2020).

The ongoing transformation of the auditing field, driven by artificial intelligence, calls for more research on its implications for the auditor's role. While the use of AI in auditing has been researched, the effects of AI automation and augmentation on the auditor's role have not been specifically explored. Scant literature has explored the automation-augmentation paradox in relation to the auditor's role. Aiming to fill this gap, this research will combine the existing literature on automation and augmentation with auditing.

While the effects of automation and augmentation on the auditor's role have not been explored explicitly in previous research, the effects of AI in auditing have been researched from other perspectives. Studies have researched AI's effects on the audit process (Fedyk et al., 2022; Kokina & Davenport, 2017; Seethamraju & Hecimovic, 2023), audit profession (Du, 2024; Rodrigues et al., 2023), audit firms (Law & Shen, 2024), audit quality (F. Y. Mpofu, 2023; Noordin et al., 2022), auditor judgement (Samiolo et al., 2024), independence conflicts (Libby & Witz, 2020), and audit experience (Mackenzie, 2025). Previous research has also examined the opportunities and challenges of AI adoption in auditing (Kokina et al., 2025; Munoko et al., 2020) with Commerford et al. (2021) explicitly focusing on the issue of algorithmic aversion. Existing research has also examined the use of other emerging technologies (Carpenter & McGregor, 2020; Kend & Nguyen, 2020; Tiberius & Hirth, 2019; Vitali & Giuliani, 2024), such as robotic process automation (RPA) (Moffitt et al., 2018), natural language processing (NLP) (Fisher et al., 2016), and machine learning (ML) (Cho et al., 2020; Ucoglu, 2020), in auditing and accounting.

While Alles and Gray (2019) have explored automation in auditing, their study focused on automation in a general sense rather than specifically AI automation, and it was focused solely on automation, not augmentation. Outside of auditing, research has been conducted on automation and augmentation (Johnson et al., 2022; Raisch & Krakowski, 2021), as well as the coexistence of humans and AI (Einola & Khoreva, 2023; Zirar et al., 2023). An exception within the auditing field is a recent study by Gu et al. (2024), where they suggest the concept of co-piloted auditing, where human auditors and AI collaborate. While their work contributes valuable insight into the relationship between human auditors and AI, they focus on conceptualising the audit process instead of examining the practical impact of AI automation and augmentation on the auditors' role. This study aims to address this gap in the literature.

Therefore, while AI use in auditing has created growing interest in research, understanding the effects of AI automation and augmentation on the auditors' role remains unexplored. This thesis aims to fill these gaps by exploring how AI automation and augmentation will affect the future role of auditors, by examining the benefits and challenges of AI automation and augmentation to international auditing firms

1.2 Research questions and delimitations

This thesis aims to explore how AI automation and augmentation will change the role of auditors in international auditing firms.

The primary research question of this thesis is:

1. How will AI automation and augmentation affect the auditor's role in international audit companies?

The secondary research questions are:

2. How will international auditing companies benefit from AI automation and augmentation?
3. How will the challenges of AI automation and augmentation affect international auditing companies?

This thesis has several delimitations. Firstly, this study focuses on international audit firms operating in Finland. Therefore, it does not address international audit firms operating in other countries. Secondly, this research focuses exclusively on external auditing, excluding internal auditing from the scope of this research (Hayes et al., 2005). Finally, for clarity, the term artificial intelligence (AI) in this thesis encompasses both traditional AI and Generative AI (GenAI). However, while RPA is frequently categorised alongside AI technologies, this thesis does not define RPA as AI, as they are fundamentally different (IBM, 2025).

1.3 Key concepts

Artificial Intelligence

Artificial intelligence (AI) can be defined as “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan & Haenlein, 2019, p.17).

External auditing

External auditing provides an independent assessment of whether an entity’s financial statements give a true and fair view of its financial situation (F. Y. Mpofu, 2023).

Automation

Automation can be defined as machines replacing tasks, such as routine tasks, that humans previously performed (Raisch & Krakowski, 2021).

Augmentation

In augmentation, the role of AI is to assist humans with tasks that require complex thinking, such as decision-making and data analysis (Raisch & Krakowski, 2021).

Human-AI coexistence

The coexistence between humans and AI has been defined as “humans and AI in the workplace ecosystem as organisational members interacting with AI-solutions, including any kind of contact or bond between people and AI generating beliefs, attitudes, emotions, and behavioral patterns once the AI-solution is implemented and as it evolves over time” (Einola & Khoreva, 2023, p.119).

Professional scepticism

Professional scepticism is a critical mindset that auditors and accountants must exercise in all assurance engagements. It involves compliance with the fundamental principles of integrity, objectivity, professional competence and due care (IESBA, 2018).

Professional judgement

Professional judgement is exercised when auditors apply their knowledge, skills and experience to make informed decisions based on the facts and circumstances. It includes assessing available information, recognising bias, and evaluating compliance with relevant principles (IESBA, 2018).

1.4 The structure of the study

This thesis is divided into eight chapters. The first chapter is the introduction, in which the topic is introduced. First, the background of the study is explained, and the research gap is presented. Then, the research questions, aims, and delimitations are presented. Finally, the key concepts are explained, and the structure of the study is displayed.

The literature review consists of three chapters. The first chapter lays the theoretical background by first defining and discussing auditing and AI, and then presenting the automation-augmentation paradox and human-AI coexistence. The second chapter describes the current use of AI in auditing as well as the benefits and challenges of AI automation and augmentation. The final theory chapter explores the changes to the future role of auditors and presents a summary of the theoretical framework.

The fifth chapter introduces the study's methodology. It presents the research method and sample and evaluates reliability and validity. The findings are gathered and presented thematically in the sixth chapter. Then, in the discussion chapter, the findings are analysed considering previous literature. The eighth and final chapter is the conclusion. In this chapter, the key findings are presented alongside theoretical and practical implications. Finally, the limitations and future research suggestions are discussed.

2 Auditing and artificial intelligence

This chapter presents the ground theory on auditing and artificial intelligence (AI). First, the auditor's current role is described by explaining the concept and purpose of auditing. Then, the auditor's responsibilities are introduced through the standard audit process model, and the organisations and standards that affect auditors' work are presented. Then, AI is defined, its subcategories are presented, and its development is explored. Finally, automation and augmentation are defined, and the concept of coexistence between humans and AI is introduced.

2.1 The auditor's role and responsibilities

According to Hayes et al. (2005) the purpose of a financial statement audit is to evaluate whether the financial statements give a true and fair view while complying with specific accounting principles. The definition given in ISA 200 states that the objective of an audit of financial statements is to enable the auditor to express an opinion on whether the financial statements are prepared, in all material respects, in accordance with a financial reporting framework (IAASB, n.d.-b). Eilifsen Aasmund et al. (2013) suggested that the main role of auditors is to give an objective opinion of whether the financial documents accurately present a true and fair view of the company's financial status.

Auditors are expected to give reasonable assurance that the financial statements do not include misstatements from fraud or error (Eilifsen Aasmund et al., 2013; Hayes et al., 2005). Reasonable assurance is a high level of assurance that is based on gathering enough suitable evidence (Hayes et al., 2005) but it does not mean absolute assurance (Eilifsen Aasmund et al., 2013). Because of the volume of transactions, considering the time and cost, auditors cannot test every transaction and, therefore, are not aiming to provide absolute assurance of the financial statements (Eilifsen Aasmund et al., 2013).

Hayes et al. (2005, p. 3) stated that "the function of auditing is to lend credibility to the financial statements". Auditing improves company credibility with banks, shareholders and customers because of its regulations and auditors' impartial opinion offers an external validation for the shared information (Eilifsen Aasmund et al., 2013). Auditing also increases transparency and trust between management and owners (Eilifsen Aasmund et al., 2013).

The auditing process can be divided into four phases (see Figure 1) based on the standard audit model presented by Hayes et al. (2005). The phases are client acceptance, planning and design of an audit approach, tests for evidence, and completion of the audit and issuance of an audit report.

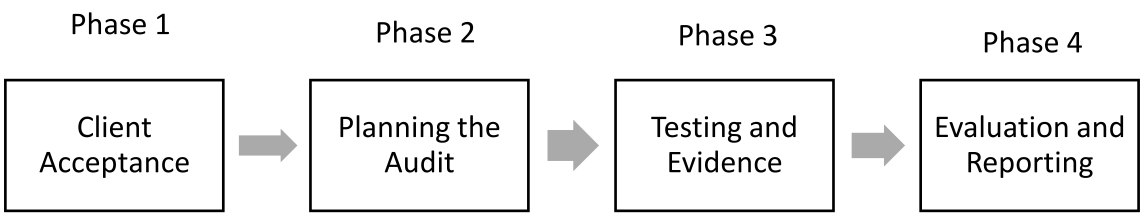

Figure 1. Standard Audit Process Model (Hayes et al., 2005).

In the client acceptance phase, the auditor accepts the client, and the client accepts the auditor (see Figure 2). The procedures for this phase include a background check of the client, ensuring there are no conflicts of interest for the auditor, selecting staff and assessing whether other professionals are needed, discussing with the previous auditor, preparing a client proposal, and finally, receiving an engagement letter stating the agreement of the audit.

In the planning phase, the auditor evaluates what and how much evidence is needed to gain reasonable assurance that the financial statements are free of material misstatement (see Figure 2). This is usually done by performing audit procedures to understand the audited entity, conducting a material misstatement risk assessment, determining materiality, preparing the audit program, and preparing a memorandum with the plan for addressing identified risks.

The testing and evidence phase tests internal controls and the fairness of financial statements (see Figure 2). It consists of control tests, transaction tests, analytical procedures, and balance detail tests, and it also looks for unrecorded liabilities.

Finally, in the audit completion phase, the evidence is evaluated, additional procedures are performed, financial statements are reviewed, and the board of directors is reported, and an audit report is prepared (see Figure 2).

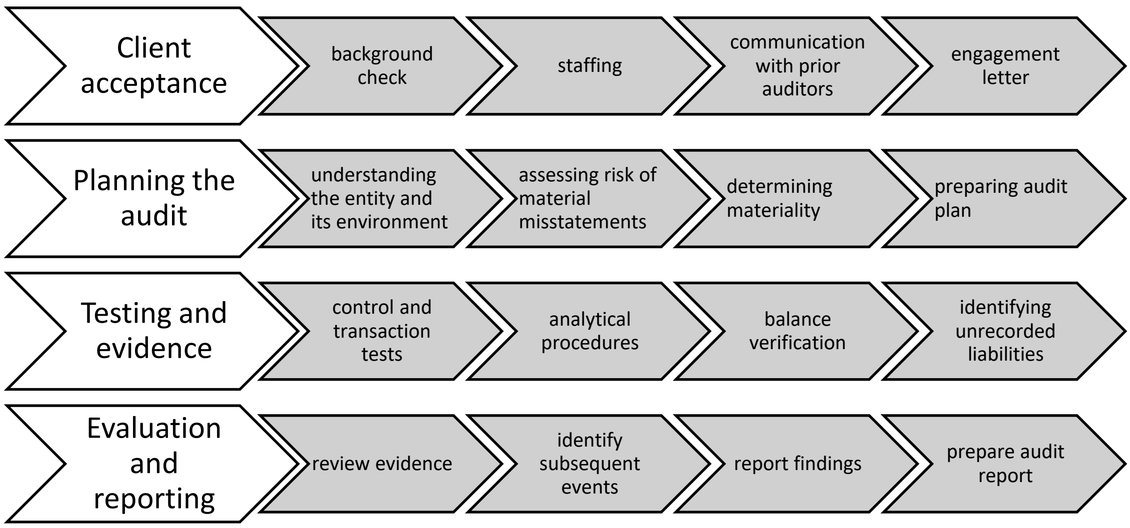

Figure 2. Standard Audit Process Model adapted from Hayes et al. (2005).

The auditing process is guided by multiple standards that auditors must follow. Internationally, the most significant ones are the International Standards on Auditing (ISA), the International Code of Ethics for Professional Accountants, and the International Financial Reporting Standards (IFRS) (Suomen Tilintarkastajat, n.d.-c). The ISA standards are auditing guidelines issued by the International Auditing and Assurance Standards Board (IAASB) (Hayes et al., 2014) that define basic audit principles and objectives and guide auditors through the audit process and documentation (Suomen Tilintarkastajat, n.d.-

c). The main purpose of IAASB is to enhance audit quality and ensure consistency across audits by establishing international standards for auditing, quality control, reviews, and other assurance services (IAASB, n.d.-a). The International Code of Ethics for Professional Accountants is issued by the International Ethics Standards Board for Accountants (IESBA), and it guides auditors' work through ethical principles that auditors must apply to all audit engagements (IESBA, n.d.; Suomen Tilintarkastajat, n.d.-a). The main ethical principles of auditing are “integrity, objectivity, professional competence and due care, confidentiality, and professional behaviour” (IESBA, n.d.). The main purpose of IESBA is to support ethics in businesses and organisations and increase trust in financial and non-financial information (IESBA, n.d.). The IFRS provide the accounting standards against which auditors must evaluate the compliance of financial statements, and they are issued by the International Accounting Standards Board (IASB) (Suomen Tilintarkastajat, n.d.-b).

2.2 The definitions and development of artificial intelligence

There are multiple definitions for AI. Nilsson (1971) defines artificial intelligence as machines that perform cognitive functions such as learning, interacting, and problem-solving, which are traditionally associated with human minds. Kaplan and Haenlein (2019, p.17) instead, define AI as “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation”. AI has also been defined as a system’s capability to recognise, construe, draw implications and study data for an organisation's economic and societal goals by Mikalef & Gupta (2021).

Mukhamediev et al. (2022) categorised AI into seven sublevels, which are machine learning (ML), planning, robotics, natural language processing (NLP), expert systems, speech and vision (see Figure 3). The most commonly discussed in the literature regarding AI use in auditing are machine learning (ML), natural language processing (NLP), optical character recognition (OCR), deep learning and Generative AI (GenAI) (Bakumenko

& Elragal, 2022; Fedyk et al., 2022; Kokina et al., 2025; F. Y. Mpofu, 2023; Samiolo et al., 2024).

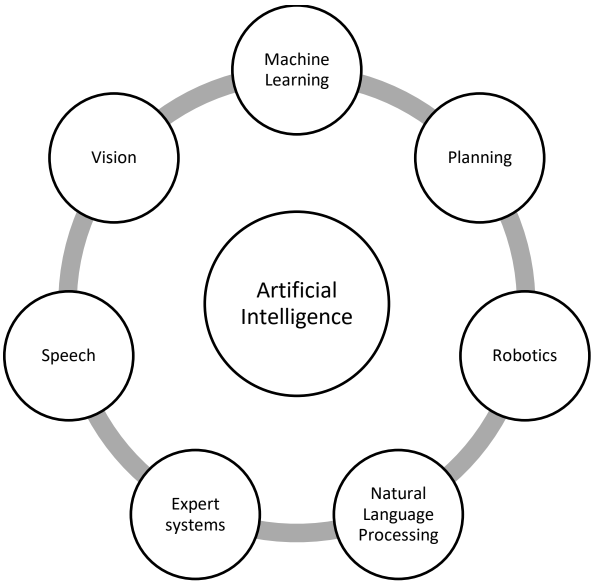

Figure 3. Sublevels of AI adapted from Mukhamediev et al. (2022)**.**

ML is a form of AI that was initially defined by Samuel (1959) as a computer's ability to learn from experience without being programmed. More recently, Ucoglu (2020) describes that ML uses algorithms and statistical methods to recognise patterns and make predictions.

NLP is an AI application that uses ML to assist computers in understanding and generating text and speech (Fisher et al., 2016; Stryker & Holdsworth, 2024).

Even though RPA is frequently categorised alongside AI technologies, it is fundamentally distinct from AI (IBM, 2025). Their main difference is that RPA is process-driven while AI is data-driven, meaning that RPA can automate tasks based on predefined rules, but AI can also learn (Zemankova, 2019). Despite this difference, RPA and AI complement each other effectively and often coexist in applications (Ribeiro et al., 2021).

GenAI is a more recently emerged subcategory of AI that can create original human-like content such as text, photos, and videos (Feuerriegel et al., 2024; Li & Liu, 2020). Unlike traditional AI tools, GenAI can provide answers for diverse and complicated questions (Lim et al., 2023). A widespread publicly open example of generative AI is Open AI's ChatGPT (Bandi et al., 2023), which was released in 2022 (Holmström & Carroll, 2024).

AI's history dates back to 1950 when Alan Turing published a transformative article exploring the question, "Can machines think?". In the article, he described how intelligent machines could be created and introduced the "Turing Test", a method for evaluating a machine's intelligence. According to the test, if a person cannot distinguish between a human and a machine during interaction, the machine is considered intelligent (TURING, 1950). Turing's groundbreaking research laid the foundation for AI research, and the "Turing Test" remains a benchmark for assessing machine intelligence (Haenlein & Kaplan, 2019).

The term "Artificial Intelligence" was introduced six years later, in 1956, at the Dartmouth Summer Research Project on artificial intelligence, which brought together researchers from various fields to establish a research area for AI (Haenlein & Kaplan, 2019). The participants of this project, including Marvin Minsky, John McCarthy, Herbert Simon, Allen Newell, Claude Shannon, Nathaniel Rochester and other scholars, can be considered the founding fathers of AI (Crevier, 1993).

After the Dartmouth Conference, the field of AI made significant advancements over the next two decades (Haenlein & Kaplan, 2019). A key development during this time was the famous ELIZA computer program created by Joseph Weizenbaum in 1966, which was an early natural language processing tool that could simulate human conversation (Weizenbaum, 1966).

However, AI development faced a setback in 1973 when James Lighthill published a report for the British Science Research Council questioning other researchers' optimistic outlook on AI (Haenlein & Kaplan, 2019). The report stated that while research on automation systems showed some value, the development was insufficient (Lighthill, 1973). It also added that robot research was ineffective, and therefore, its cancellation was recommended. The report's findings caused uncertainties, resulting in cuts in AI funding and a decrease in AI development, commonly called the "AI Winter" (Haenlein & Kaplan, 2019). However, in 1997, an IBM Deep Blue chess-playing program defeated the chess world champion, Gary Kasparov (Campbell et al., 2002) proving that previous claims by Lighthill (1973) were not entirely correct.

The rise of big data brought significant advancements to AI in the early 2000s, resulting in AI's integration into different business fields (Haenlein & Kaplan, 2019). AI has been increasingly adopted into businesses during the last decade. A report by McKinsey & Company (2024) showed that AI implementation has grown from 55% in 2023 to 78% in 2024 (see Figure 4), showing a remarkable growth in one year. Before that, the last drastic change was from 20% in 2017 to 47% in 2018. otherwise the adoption percentage has had little deviation between 47% and 55%.

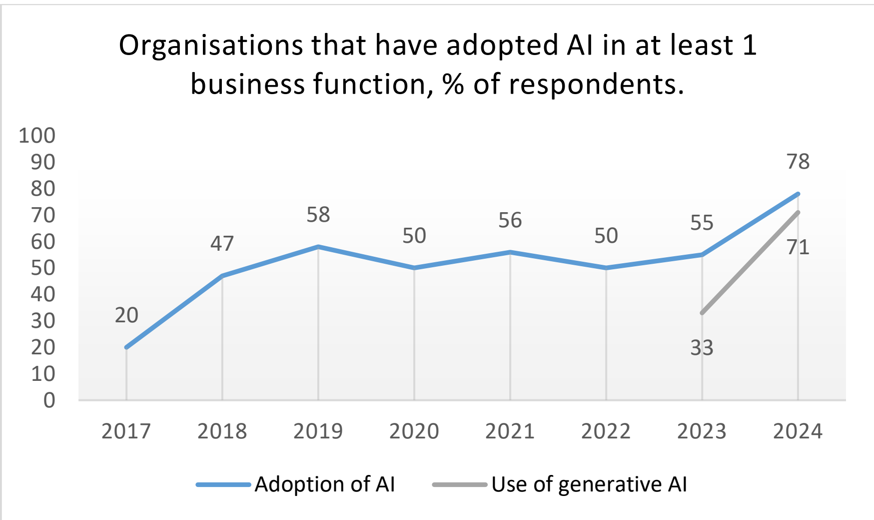

Figure 4. AI adoption in organisations 2017-2024 (McKinsey & Company, 2024)**.**

AI development has made remarkable advancements in recent years, with the emergence of generative AI (Stryker & Scapicchio, 2024). Generative AI can create and analyse unstructured data such as text, images and audio that is indistinguishable from human work, which has challenged previous beliefs that creative tasks such as writing and drawing can only be done by humans (Feuerriegel et al., 2024). The report by McKinsey and Company (2024) also shows the increase in generative AI adoption, as its use has doubled from 2023 to 2024 (see Figure 4), indicating its potential for organisations.

2.3 AI automation and augmentation

Organisations' AI applications can be divided into automation and augmentation (Daugherty & Wilson, 2018). Automation can be referred to as machines replacing tasks that were previously done by humans (Davenport & Ronanki, 2018; Raisch & Krakowski, 2021), while augmentation can be referred to as close collaboration between machines and humans (Raisch & Krakowski, 2021), which enables machines to be complemented with human-specific skills such as common sense and intuition (Daugherty & Wilson, 2018). Augmentation, unlike automation, requires continuous cooperation between machines and humans (Amershi et al., 2014) to combine their strengths to solve challenging tasks (Johnson et al., 2022). Whether a task is automated or augmented is determined by the nature and complexity of the task (Raisch & Krakowski, 2021). According to Daugherty & Wilson (2018), well-structured routine tasks can be automated and Kim et al. (2017) agree as they stated that routine tasks with little human communication that do not require high education and training can be automated. According to Daugherty and Wilson (2018), more complex and undefined tasks can be augmented.

Raisch and Krakowski (2021) found that even though automation and augmentation are often viewed as opposing forces, they are very interdependent. They proposed a paradoxical view of automation and augmentation to support this theory, challenging the usual trade-off view that organisations must choose between the two. They believe that augmentation supports automation, and automation supports augmentation, continuously evolving and improving each other. They also mention that a previously augmented task can sometimes become automated over time as the interaction between AI and managers increases the AI’s knowledge. Einola and Khoreva (2023) also made significant findings on the connection between automation and augmentation. They found that automation and augmentation cannot be separated as they are interconnected and exist together everywhere, which only partly supports Raisch and Krakowski's (2021) paradox view on automation and augmentation.

Raisch and Krakowski (2021) found that improved interdependency between automation and augmentation could lead to organisational and societal benefits through a positive cycle of selective deskilling and strategic requalification. This means that humans eliminate tasks that machines can do better and instead focus on improving their unique strengths.

Holmström and Carroll (2024) instead, presented a typology matrix specifically for GenAI, which consists of four innovation strategies based on their level of automation and augmentation (see Figure 5). The four innovation strategies are traditional tools, basic automation, automated assistance, and assisted augmentation. Traditional tools involve low automation and augmentation as they do not use advanced technologies and rely on human expertise. Basic automation involves high automation and low augmentation, focusing on automating routine tasks and improving efficiency with technology. Automated assistance intends to augment human capabilities by enhancing human skills through technology, using high augmentation and low automation. Lastly, assisted augmentation includes a high level of automation and augmentation as it uses advanced technologies to improve human capabilities by automating parts of the process while augmenting human skills.

		AUGMENTATION	
		LOW	HIGH
AUTOMATION	HIGH	Basic automation	Assisted augmentation
	LOW	Traditional tool	Automated assistance

Figure 5. A typology matrix for generative AI by Holmström and Carroll (2024).

2.4 The coexistence of humans and artificial intelligence

Einola and Khoreva (2023) defined the coexistence between humans and AI as employees interacting with AI systems, creating connections that generate attitudes, emotions, beliefs and behaviours. They emphasise that the coexistence between humans and AI is a changing and evolving system that involves constant adaptation. This supports Beer's (2017) findings, which state that the relationship between humans and machines is recursive, as humans shape machine algorithms and machines shape human behaviour. Deng et al. (2017) specify that AI is constantly influenced by human actions such as defining objectives, curating data and giving feedback, while Moser et al. (2022) state that humans are similarly affected by AI as it provides information and guidance, ultimately affecting human judgement. While there are multiple studies on how businesses can benefit from AI, there is still limited research on the coexistence of humans and AI (Zirar et al., 2023).

Raisch and Krakowski (2021) define successful coexistence as one in which AI and employees augment each other's capabilities so that both can focus on their inherent strengths. Shrestha et al. (2021) found that this benefits both the organisation and employees as AI can be trained to handle time-consuming repetitive tasks, leaving employees more time to focus on their human capabilities, such as critical thinking and decision-making. Einola and Khoreva (2023) believe that the coexistence of humans and AI will eventually lead to hybrid workplaces in which humans and AI work so closely together that it is difficult to distinguish their contributions.

Studies by Zirar et al. (2023) and Einola and Khoreva (2023) found that the coexistence of humans and AI is necessary. To successfully implement AI and human coexistence into the workplace, Zirar et al. (2023) suggest that organisations must provide sufficient training for workers to gain technical, human and conceptual skills and to adapt to new job roles within a technologically evolving environment. Einola and Khoreva (2023) highlight that effective coexistence between humans and AI also requires synchronisation with external stakeholders such as customers and supply chain partners.

3 Artificial intelligence in auditing

This chapter examines AI in auditing. First, it discusses AI's current application in auditing, then it explores the benefits and challenges associated with AI automation and augmentation.

3.1 Current use of artificial intelligence in auditing

Assessing current AI use in auditing is challenging due to the limited differentiation between AI's potential and actual implementation in research. Also, the findings on the extent of current AI use in auditing vary slightly. Fedyk et al. (2022) reported that technology, including traditional AI, is widely used in auditing firms, while Samiolo et al. (2024) stated that the actual use of AI is limited to traditional AI with simple ML tools. Very recently, Kokina et al. (2025) found that while large auditing firms are using different AI technologies, the implementation of AI in auditing is still in the early phases of development. They found that traditional AI tools, such as ML and NLP, are widely used in auditing, while complex AI tools, such as GenAI, are in the experimental phase and have not yet been implemented into core audit procedures. They believe GenAI's implementation into audit processes will likely be slow and require human supervision due to uncertainty in GenAI's outputs. AI adoption is also affected by barriers such as a lack of transparency (Seethamraju & Hecimovic, 2023) and regulation (Kokina et al., 2025), which will be further discussed in the challenges chapter.

AI technologies are currently used to automate and augment various tasks (see Table 1). The most used AI technology in auditing is ML, which is commonly used for anomaly detection and document comparison (Fedyk et al., 2022; Kokina et al., 2025; Samiolo et al., 2024). Other AI technologies currently used are NLP, OCR, and GenAI. NLP is used to review and generate financial statements and extract key information from contracts and documents (Kokina et al., 2025), and OCR is used for reviewing contracts and documents (Fedyk et al., 2022). GenAI is used for supportive tasks such as question-and-answer tools and report generation (Kokina et al., 2025). The current AI applications in auditing are mostly seen as augmentation instead of automation. Research by Munoko et al. (2020) reports that most current AI applications can be considered augmentation with a few exceptions. Similarly, Kokina et al. (2025) found that by far, AI use in auditing has been augmentation instead of automation.

Kokina et al. (2025) report that the extent of AI use in auditing differs between Big 4 and non-Big 4 firms. The findings by Seethamraju and Hecimovic (2023) also show that Big 4 firms are investing more in AI development than mid-tier audit firms. They found that mid-tier audit companies are more hesitant to implement AI into their audit practices due to a lack of knowledge and financial resources.

Table 1. Current use of AI technologies in auditing. Compiled by the author from multiple sources.

AI technology	Use
NLP	Extracting information from documents
	Reading and generating financial statements
OCR	Document review
ML	Anomaly detection
	Document comparison and matching
GenAI	Question and answer tools
	Report generation

3.2 The benefits and challenges of artificial intelligence in auditing

AI use in auditing can offer audit firms significant benefits and challenges. Even though automation and augmentation are often discussed separately, they cannot be entirely separated because they are deeply connected (Einola & Khoreva, 2023; Raisch & Krakowski, 2021). Their interdependence makes it challenging to separate the effects of automation and augmentation. However, the benefits and challenges will be loosely categorised based on the definitions by Raisch and Krakowski (2021) while acknowledging

Einola and Khoreva’s (2023) view that automation and augmentation cannot be separated, as they consist of each other.

3.2.1 Benefits of artificial intelligence in auditing

Multiple studies agree that AI can bring significant benefits to auditing (Abdullah & Almaqtari, 2024). However, as AI use in auditing is still at an early stage (Kokina et al., 2025), a lot of research focuses on the potential benefits that AI can bring to auditing instead of presenting perceived benefits. Du (2024) highlights the limitations of traditional auditing, including the risk of human error, challenges in detecting complex fraud, and time-consuming inspection procedures. The use of AI can address these limitations, as AI can reduce human error, increase efficiency and improve fraud detection (Vitali & Giuliani, 2024).

AI's most common perceived or potential benefits in auditing can be broadly categorised into those driven by automation and those enabled by augmentation. Mainly, automation-related benefits include increased efficiency (Abdullah & Almaqtari, 2024; Du, 2024; Fedyk et al., 2022; F. Y. Mpofu, 2023; Nguyen et al., 2024; O’donnell, 2024; Seethamraju & Hecimovic, 2023; Vitali & Giuliani, 2024) and improved audit quality (Abdullah & Almaqtari, 2024; Du, 2024; Fedyk et al., 2022; F. Y. Mpofu, 2023; Nguyen et al., 2024; Seethamraju & Hecimovic, 2023; Vitali & Giuliani, 2024). Automating routine tasks also frees auditors' time and allows them to focus on more complex areas that require human judgement (Fedyk et al., 2022; F. Y. Mpofu, 2023; Seethamraju & Hecimovic, 2023; Vitali & Giuliani, 2024), which augments human cognition. AI augmentation can enhance risk management (F. Y. Mpofu, 2023; Vitali & Giuliani, 2024) and improve decision-making (Abdullah & Almaqtari, 2024; Seethamraju & Hecimovic, 2023; Vitali & Giuliani, 2024), thereby also contributing to audit quality.

The automation of routine tasks can increase the efficiency and quality of audits. AI can perform routine tasks faster and more accurately than human auditors, which can lead to increased efficiency and quality (F. Y. Mpofu, 2023). A study by Fedyk et al. (2022) found that using AI reduces manual work by speeding up processes such as data analysis and testing, which can result in improved efficiency over time. Supporting claims were made by Noordin et al. (2022), who state that AI can increase efficiency by automating tasks such as data entry and analysis. Research by Seethamraju and Hecimovic (2023) suggests that automation reduces the time auditors spend on manual tasks, which can improve the efficiency and effectiveness of the audit process. Similar results were discovered by Vitali and Giuliani (2024) who found that by automating routine tasks, auditors can perform audits more efficiently, resulting in fewer mistakes.

In addition to these benefits, automating manual tasks also frees auditors' time and allows them to focus on more complex tasks requiring human judgement, which can improve audit quality and decision-making (Zhang, 2019). Fedyk et al. (2022) also report an increase in audit quality resulting from auditors' decreased routine tasks, allowing them to focus on the most important tasks. Similarly, Vitali and Giuliani (2024) highlight that automation enables auditors to concentrate on areas such as funds and depreciation that require professional judgement. Seethamraju and Hecimovic (2023) concluded that automation enables auditors to make better judgements and increases audit quality.

The use of AI technologies in auditing can reduce the risk of material misstatement and improve fraud detection. F. Y. Mpofu (2023) states that AI can improve fraud detection by detecting high-risk transactions and questionable income and expenses. ML algorithms can analyse large datasets to find anomalies, patterns, and outliers and flag transactions that could indicate errors, fraud, or compliance issues for human inspection (Bakumenko & Elragal, 2022; F. Y. Mpofu, 2023). Vitali and Giuliani (2024) report that audit risks can be reduced by AI's ability to augment auditors' decision-making through distinguishing anomalies and relationships beyond human capabilities. AI technologies allow auditors to offer increased assurance by testing 100% of the population instead of sampling, which can also improve the overall quality of the audit (Kend & Nguyen, 2020). F. Y. Mpofu (2023) highlights that the risk of material misstatement is lowered when testing the whole population. The research by Fedyk et al. (2022) supports this claim as its empirical findings showed that audit firms investing in AI had fewer restatements.

3.2.2 Challenges of artificial intelligence in auditing

While the literature widely discusses AI's benefits in auditing, its adoption also presents significant challenges for auditing firms. Common challenges of AI use in auditing include a lack of transparency (Kokina et al., 2025; F. Y. Mpofu, 2023; Munoko et al., 2020; Seethamraju & Hecimovic, 2023), confidentiality and data security concerns (Kokina et al., 2025; F. Y. Mpofu, 2023; Munoko et al., 2020), biases (Kokina et al., 2025; Munoko et al., 2020; Seethamraju & Hecimovic, 2023), under- and overreliance (Commerford et al., 2021; Kokina et al., 2025; F. Y. Mpofu, 2023), deskilling (Munoko et al., 2020; Seethamraju & Hecimovic, 2023), and regulatory uncertainty (Kokina et al., 2025; Munoko et al., 2020).

Some of these challenges, such as lack of transparency, data security, algorithmic bias, and the absence of regulation, apply to both automation and augmentation. However, certain challenges can be associated with automation or augmentation specifically. For instance, underreliance on AI mainly relates to augmentation, as it occurs when auditors lack trust in AI-generated insights. In contrast, deskilling from overreliance on AI is associated with automation, as task automation may result in fewer learning opportunities for junior auditors.

The lack of transparency and explainability in AI systems creates challenges regarding trust in AI outputs (F. Y. Mpofu, 2023). Kokina et al. (2025) bring up the challenge of explaining AI output in order to trust the accuracy of AI-generated results. Munoko et al. (2020) also highlight the importance of transparency in auditing, as auditors should be able to present the reasoning behind their decisions, which is currently difficult due to

AI’s “black box” nature. Seethamraju and Hecimovic (2023) note that AI’s output should be transparent and explainable in order to effectively implement AI in auditing.

The use of AI tools in auditing raises concerns about data security and confidentiality, as AI tools must be trained with data. A literature review by F. Y. Mpofu (2023) concluded that using AI tools in auditing can compromise confidentiality, which is one of the main ethical principles in auditing included in the International Code of Ethics for Professional Accountants (IESBA, 2018). Munoko et al. (2020) highlight that audit firms must ensure data security when using client data in AI tools, and they also raise an ethical question about how the data for AI training is obtained. They remind that auditors must secure client data from potential data breaches to avoid compromising confidentiality. Kokina et al. (2025) also highlight the challenge of ensuring ethical AI tool training and client data privacy. Their findings suggest using publicly available data for AI model training to mitigate this risk.

The risk of biased results poses significant challenges to the application of AI in auditing (Seethamraju & Hecimovic, 2023). According to the ethical standards for accounting IESBA (2018), auditors should maintain their professional judgement and not let biases influence their decisions to ensure objectivity. Munoko et al. (2020) identify that biased training data can lead to compromised objectivity. AI algorithms base their results on training data, which means that AI algorithms can produce prejudiced answers if the training data does not represent the population correctly, which can affect the fairness and impartiality of the audit (Kokina et al., 2025). To avoid algorithmic bias, Munoko et al. (2020) suggest that audit firms should have appropriate quality control systems for AI algorithm supervision.

The use of AI in auditing creates concerns about auditors' over- and underreliance. Commerford et al. (2021) found that auditors are more likely to trust evidence from human specialists than AI algorithms. This distrust can result in auditors dismissing AI evidence, compromising the audit's accuracy and quality. The authors highlight that human auditors must trust AI in order to receive benefits from its use. F. Y. Mpofu (2023) presents that audit quality can be affected by auditors' distrust in AI-generated evidence when it is accurate and, contrastingly, their trust in weak AI-generated evidence, which aligns with the findings by Commerford et al. (2021). To avoid overreliance on AI tools, Kokina et al. (2025) remind that auditors should always apply professional scepticism and judgement when using AI tools.

Overreliance on AI can also create the risk of auditor deskilling. According to Sutton et al. (2023), deskilling can occur in new professionals who lack knowledge usually gained through experience, or in professionals who lose skills that have once been acquired due to a lack of use. In the auditing context, Munoko et al. (2020) consider that as AI automates routine tasks, beginner auditors might not acquire all the skills and experience previously learned through these tasks. Similarly, Seethamraju and Hecimovic (2023) discuss the possible deskilling effect arising from low-level task automation, as junior auditors will lose learning opportunities.

The lack of regulation on AI use in auditing poses a challenge and can also be considered a barrier to AI implementation. Munoko et al. (2020) mention the lacking governance of AI use in auditing, which leaves audit firms unsure of the expected measures around AI use. Similarly, Kokina et al. (2025) note that there are currently no regulations on the use of AI in auditing, and audit regulators are only considering creating regulations on this subject. They suggest that auditing regulators should consider ethical AI use in auditing and provide audit firms with practical guidance.

4 The future role of auditors

This chapter explores how AI is reshaping the role of auditors. First, it addresses whether AI will replace or assist auditors and examines how AI will transform auditing and auditors' responsibilities. Finally, it outlines the most important competences for auditors to succeed in the future.

4.1 The evolving role and responsibilities of auditors

The fast implementation of AI technologies in auditing has raised concerns about the future role of human auditors and the possibility of job displacement due to automation (Du, 2024). A study by Frey and Osborne (2017) reported that auditing is one of the jobs most likely to be replaced by computerisation. A World Economic Forum (2015) report instead predicted that AI could perform 30% of corporate audits by 2025, highlighting the capabilities of AI automation. Despite concerns about job replacement, most studies agree that AI will not replace auditors with automation but instead assist them and augment their capabilities (Dhamija & Bag, 2020; Hasan, 2022; Law & Shen, 2024; Mackenzie, 2025; Nguyen et al., 2024; Tiberius & Hirth, 2019; Vitali & Giuliani, 2024).

Previous research believes that some human elements cannot be replaced despite AI's capabilities. Mackenzie (2025) believes that the human element cannot be replaced due to auditing's people-driven nature. Vitali and Giuliani (2024) do not see AI as a threat to auditing because it cannot replace human judgement. Similarly, Hasan (2022) expresses that auditors' creativity and judgement cannot be replaced. Supporting these views, Nguyen et al. (2024) believe that professional judgement and scepticism are irreplaceable.

While most research agrees that AI cannot completely replace auditors, a common belief is that the use of AI in auditing could result in fewer auditors. Vitali and Giuliani (2024) reported that the number of entry- or mid-level auditors could decrease. Davenport and Miller (2022) speculate that, while unlikely, the widespread adoption of automation could reduce the need for entry-level auditors. Fedyk et al. (2022) found supporting evidence that AI has displaced accountants and auditors at the junior level, while higher-level auditors seem unaffected. In contrast, research by Law and Shen (2024) found evidence that AI use can increase the number of auditors. They report that using AI in auditing can create more job opportunities for auditors, as AI can create business growth and require auditors to have more complex skills.

The implementation of AI is introducing a new era of auditing where humans and AI coexist and work as a team (F. Y. Mpofu, 2023). Recently Gu et al. (2024) introduced the concept of co-piloted auditing, where auditors and AI systems work together in a continuous and iterative process. They describe co-piloted auditing as humans and AI augmenting each other's strengths to enhance audit quality and effectiveness. Similarly, Law and Shen (2024) stated that AI is not the autopilot in auditing, but instead it can be considered a copilot as it augments human competence without replacing it. The concept of co-piloted auditing is similar to the concept of coexistence. Einola and Khoreva (2023, p.119) define the coexistence of AI and humans as "organizational members interacting with AI solutions, including any kind of contact or bond between people and AI generating beliefs, attitudes, emotions, and behavioral patterns once the AI-solution is implemented and as it evolves over time". Similarly to co-piloted auditing, coexistence is an evolving process that adapts constantly (Einola & Khoreva, 2023).

Many studies agree that the audit profession will be transformed with the rise of AI. Zhang et al. (2020) believe that emerging technologies, including AI, can revolutionise auditing. Meanwhile, Libby and Witz (2020) expect emerging technologies to challenge traditional auditing methods, highlighting the need for adaptation. Hasan (2022) expects a dramatic shift in the auditor's responsibilities in the next ten years. Abu Huson et al. (2024) believe that AI will change the auditors' role and create new tasks for auditors. Similar results have been made by Kokina et al. (2025), who found that the broad adoption of AI systems has led to changes in auditing processes and the auditor's role. While many studies agree that AI will transform the audit profession, the literature is unclear on how the future of the audit profession will look (Rodrigues et al., 2023).

The use of AI in auditing is expected to change auditors’ responsibilities. One significant anticipated change is that the automation of routine tasks will shift auditors' focus from manual tasks towards more important areas (Fedyk et al., 2022) that require professional judgement (Vitali & Giuliani, 2024) and critical evaluation (Kend & Nguyen, 2020). Multiple studies also expect that auditors’ work will include working alongside machines. Kokina and Davenport (2017) believe that the auditor's future role will include tasks such as AI tool development, machine performance monitoring, and evaluation of the suitability of automation tools. More recently, Kokina et al. (2025) found that automating audit tasks will shift auditors’ focus toward conducting detailed investigations, supervising machines, and verifying the accuracy of AI-assisted audits. Moffitt et al. (2018) also state that the auditors’ role is shifting from collecting, processing, and analysing data to evaluating the results of automated procedures.

Many studies also suggest that AI could expand auditing to include continuous auditing and advisory services. Tiberius and Hirth (2019) believe that the traditional periodic audit will likely transform and shift into continuous, real-time auditing. Similarly, Leocádio et al. (2024) found that AI enables auditing to change from retrospective examination into real-time monitoring. F. Y. Mpofu (2023) found that while AI can replace humans in some areas, such as automating routine tasks, it will also open the possibility for advisory and consulting services. These findings are supported by Abu Huson et al. (2024) and Nguyen et al. (2024), who believe that changes in auditors’ roles due to AI could shift auditors toward advisory and consulting services. Seethamraju and Hecimovic (2023) support these findings by highlighting AI’s possibilities in expanding audit firms’ functions into both continuous auditing and offering consulting services.

4.2 Auditors’ future skills and competences

The changes in the auditor's role and responsibilities due to AI implementation also affect the competences that auditors should possess in order to succeed in an AI-driven environment (Law & Shen, 2024; Moffitt et al., 2018). The most mentioned skills and competences relevant for auditors in the future are technical (Lombardi et al., 2015; Nguyen et al., 2024; Sanoran & Ruangprapun, 2023; Vitali & Giuliani, 2024) and human-specific skills, such as soft skills (Law & Shen, 2024) and professional scepticism and judgement (Abu Huson et al., 2024; Hasan, 2022).

In the future, technical skills such as data analytics and IT skills will be essential for auditors (see Figure 6). Lombardi et al. (2015) believe that the development of technical skills through frequent training is essential. Sanoran and Ruangprapun (2023) also report that proficiency in data analytics and AI technologies will be important for the effective use of AI tools. Similarly, Vitali and Giuliani (2024) and Nguyen et al. (2024) suggest that auditors will have to learn IT and data-analytic skills in the future.

Human-specific skills will also be increasingly important for auditors in the future (see Figure 6). Hasan (2022) highlights the importance of human-specific skills by stating that the use of AI technologies will make auditors' judgement and professional scepticism even more important. Similarly, Abu Huson et al. (2024) express the need for auditors to develop professional scepticism, judgement, and critical thinking to succeed in the changing audit environment. Law and Shen (2024) also highlight that AI use will increase the need for auditors to have soft skills such as cognitive capabilities and customer service capabilities.

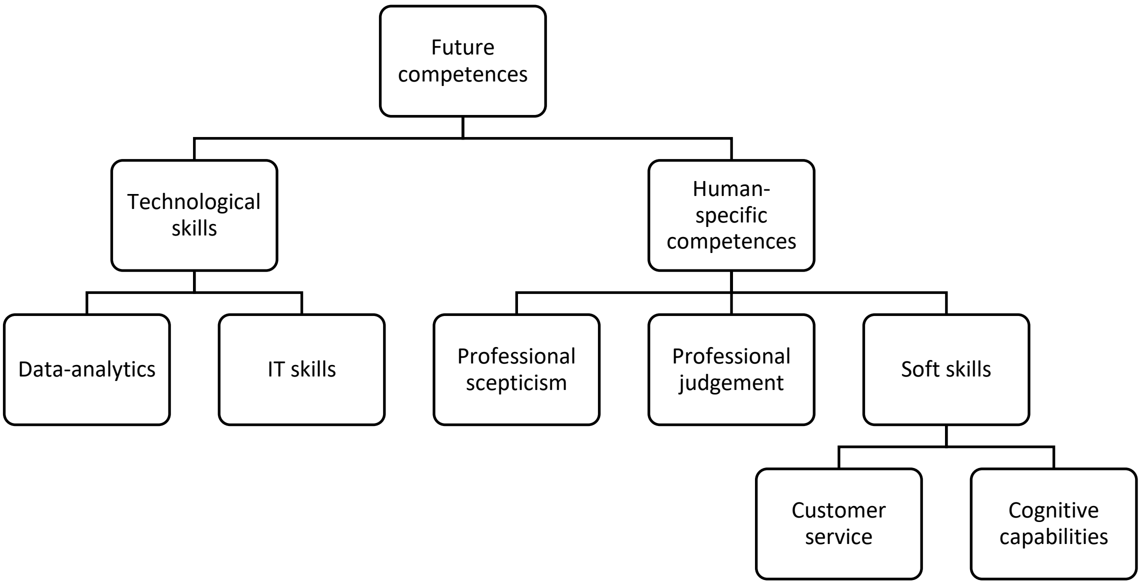

Figure 6. Future auditor competences and skills. Compiled by the author from multiple sources.

4.3 Summary of the theoretical framework

The presented theoretical framework (see Figure 7) combines the key theories and concepts regarding how AI can affect the role of auditors. Specifically, it addresses the theory in the light of the three research questions: (1) how will AI automation and augmentation affect the auditors' role in international audit companies, (2) how will international auditing companies benefit from AI automation and augmentation, and (3) how will the challenges of AI automation and augmentation affect international auditing companies.

Understanding auditors' responsibilities is essential to assessing potential changes to their role. According to Hayes et al. (2005), the primary purpose of auditors is to provide reasonable assurance of the trueness and fairness of financial statements. They created a standard auditing process model with four phases: client acceptance, planning, testing, and evidence. The auditing process is guided by multiple standards, of which the most essential are the ISA standards (Hayes et al., 2014).

The definition of AI is also important when evaluating AI's effect on the auditor's role. While there is no single definition for AI, Nilsson (1971) defines it as machines that perform cognitive functions usually associated with human minds, including learning, interacting, and problem-solving. Previous literature on AI use in auditing mainly focuses on traditional AI, such as ML and NLP (Fedyk et al., 2022; Samiolo et al., 2024), but recent research is also starting to include GenAI (Anica-Popa et al., 2024; Kokina et al., 2025).

As presented in Figure 7, the theoretical framework is based on the automation-augmentation paradox by Raisch and Krakowski (2021). They define automation as machines replacing tasks previously done by humans, and augmentation as collaboration between humans and AI where both enhance each other's capabilities. They suggest a paradoxical view on automation and augmentation because they are interconnected and cannot be completely separated. Einola and Khoreva (2023) only partly supports the paradoxical view and suggests that automation and augmentation cannot be separated at all, as they exist everywhere together.

Augmentation is closely linked to human and AI coexistence, which is another essential concept of this study (see Figure 7). Coexistence, defined by Einola and Khoreva (2023), is a close collaborative interaction between employees and AI. When successful, it benefits organisations as AI and employees augment each other's capabilities (Raisch & Krakowski, 2021), leaving employees more time to focus on human-specific skills (Shrestha et al., 2021). Einola and Khoreva (2023) suggest that this coexistence between humans and AI eventually leads to hybrid workplaces where humans and AI work so closely together that it is difficult to distinguish their contributions. They also believe coexistence can change, replace and create new job roles for humans.

To understand the effects of AI use on the auditor's role, the benefits and challenges of AI should be explored. The use of AI in auditing can bring significant benefits to auditing companies. Automation-related benefits include increased efficiency (Abdullah & Almaqtari, 2024; Du, 2024; Fedyk et al., 2022; F. Y. Mpofu, 2023; Nguyen et al., 2024;

O’donnell, 2024; Seethamraju & Hecimovic, 2023; Vitali & Giuliani, 2024) and improved audit quality (Abdullah & Almaqtari, 2024; Du, 2024; Fedyk et al., 2022; F. Y. Mpofu, 2023; Nguyen et al., 2024; Seethamraju & Hecimovic, 2023; Vitali & Giuliani, 2024). The automation of routine tasks also frees auditors' time, allowing them to focus on more complex areas that require human judgement (Fedyk et al., 2022; F. Y. Mpofu, 2023; Seethamraju & Hecimovic, 2023; Vitali & Giuliani, 2024). Augmentation-related benefits include enhanced risk management (F. Y. Mpofu, 2023; Vitali & Giuliani, 2024) and improved decision-making (Abdullah & Almaqtari, 2024; Seethamraju & Hecimovic, 2023; Vitali & Giuliani, 2024), which can also contribute to audit quality.

Despite these benefits, the use of AI can also create challenges for audit firms. Challenges that are not specific to automation or augmentation include a lack of transparency (Kokina et al., 2025; F. Y. Mpofu, 2023; Munoko et al., 2020; Seethamraju & Hecimovic, 2023), confidentiality and data security concerns (Kokina et al., 2025; F. Y. Mpofu, 2023; Munoko et al., 2020), biases (Kokina et al., 2025; Munoko et al., 2020; Seethamraju & Hecimovic, 2023), and a lack of regulation (Kokina et al., 2025; Munoko et al., 2020). However, some challenges can be more related to automation or augmentation. Overreliance (Commerford et al., 2021; Kokina et al., 2025; F. Y. Mpofu, 2023) and deskilling (Munoko et al., 2020; Seethamraju & Hecimovic, 2023) could be considered automation-driven challenges, whereas the risk of underreliance (Commerford et al., 2021; Kokina et al., 2025; F. Y. Mpofu, 2023) is more related to augmentation.

While the implementation of AI technologies in auditing raises concerns about job displacement (Du, 2024), the majority of studies agree that AI will not replace auditors, but instead assist them and augment their skills (Dhamija & Bag, 2020; Hasan, 2022; Law & Shen, 2024; Mackenzie, 2025; Nguyen et al., 2024; Tiberius & Hirth, 2019; Vitali & Giuliani, 2024). Many studies highlight that AI cannot replace some human elements, such as creativity (Hasan, 2022), judgement (Nguyen et al., 2024; Vitali & Giuliani, 2024), and professional scepticism (Nguyen et al., 2024). However, the use of AI could affect the number of auditors in the future. The common belief is that the use of AI could decrease the number of auditors, especially in the entry-level (Davenport & Miller, 2022; Fedyk et al., 2022; Vitali & Giuliani, 2024). In contrast, Law and Shen (2024) suggest that AI use could instead increase the number of auditors due to increased skill demands.

While human auditors remain necessary in the future, their role and responsibilities are expected to change with the use of AI in auditing (Abu Huson et al., 2024; Hasan, 2022; Kokina et al., 2025; Libby & Witz, 2020; Zhang et al., 2020). The automation of routine tasks shifts auditors' focus to areas that require human judgement (Nguyen et al., 2024; Vitali & Giuliani, 2024). The future role of auditors will involve working alongside AI, as auditors' responsibilities are changing from collecting, processing and analysing data to supervising machines and evaluating AI-generated results (Kokina et al., 2025; Moffitt et al., 2018). The use of AI can also expand the service offering of auditing into continuous auditing (Leocádio et al., 2024; Tiberius & Hirth, 2019) and advisory services (Abu Huson et al., 2024; F. Y. Mpofu, 2023; Nguyen et al., 2024), which opens new opportunities for audit firms and auditors.

Successful coexistence between AI and human auditors will be essential in the future as auditors work closely with AI. To navigate human-AI collaboration in auditing, Gu et al. (2024) introduce the model of co-piloted auditing, where auditors and AI work together, augmenting each other’s capabilities to reach improved audit results. This concept of co-piloted auditing is very similar to the broader concept of human-AI coexistence by Einola and Khoreva (2023), which was previously discussed.

These changes in auditors’ responsibilities mean that auditors must also update their skills and competences to succeed in a technology-driven environment (Law & Shen, 2024; Moffitt et al., 2018). The most relevant competences for auditors in the future are technical skills (Lombardi et al., 2015; Nguyen et al., 2024; Sanoran & Ruangprapun, 2023; Vitali & Giuliani, 2024) and human-specific skills, such as soft skills (Law & Shen, 2024), professional scepticism, and judgement (Abu Huson et al., 2024; Hasan, 2022).

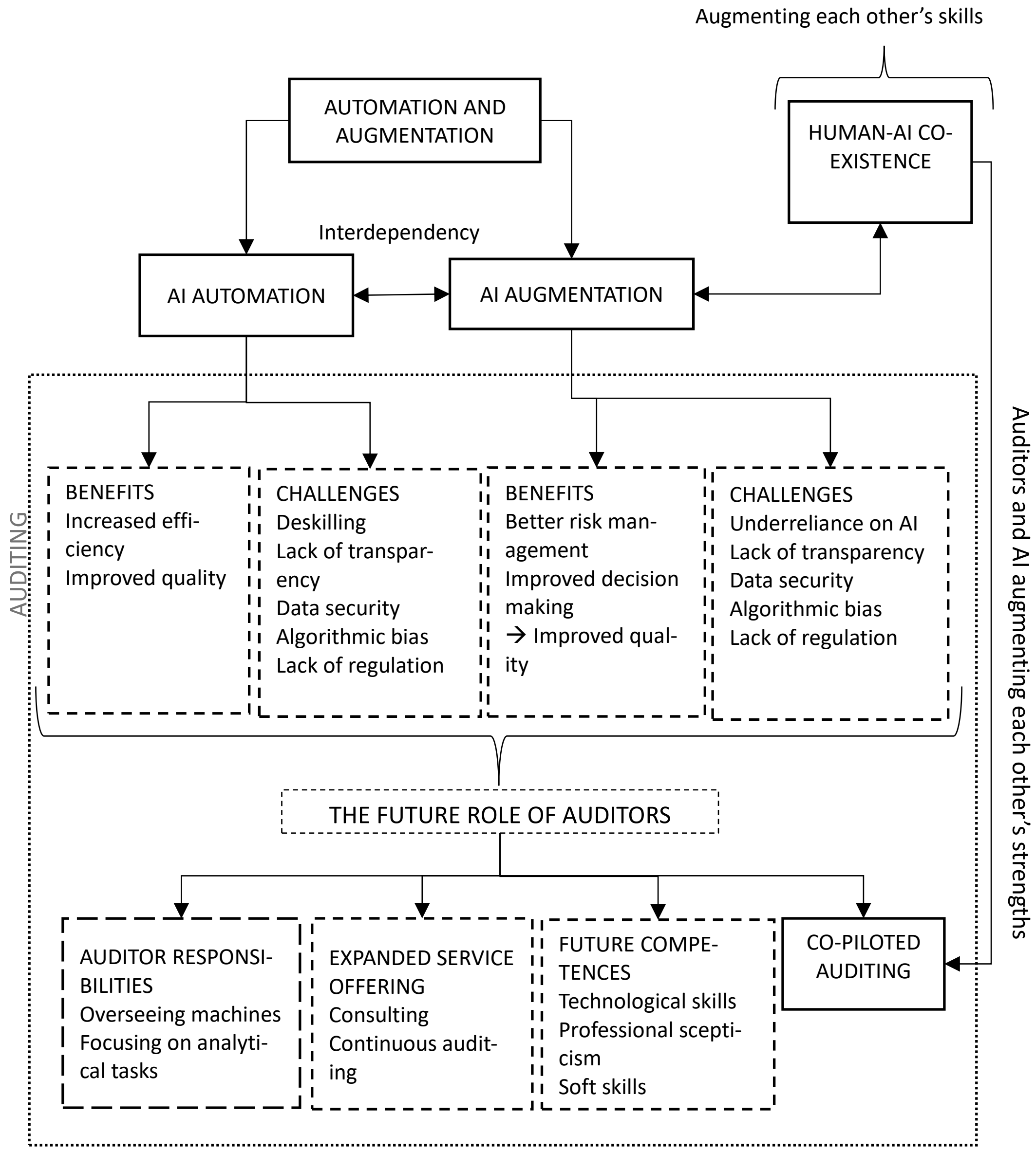

Figure 7. Theoretical framework of the thesis.

5 Methodology

This chapter presents the chosen methodology of the thesis and its justifications. First, the research methodology is presented, following the structure of the research onion by Saunders et al. (2023), which consists of philosophy, approach, method, strategy, and time horizon. Then, the data collection method and sample are introduced, followed by the data analysis method. Finally, the reliability and validity of the study are evaluated.

5.1 Research design

Before conducting research, a research philosophy should be considered, as it determines the perspective from which the study is approached (Eriksson & Kovalainen, 2008; Saunders et al., 2023). This study adopts an interpretivist approach commonly used in qualitative research to create a deeper understanding of a specific situation (Goldkuhl, 2012). Interpretivism considers humans to be different from physical phenomena because they create and interpret meanings in a social context (Alharahsheh & Pius, 2020). It is based on subjectivist assumptions, aiming to create multiple interpretations by focusing on complexity and richness (Eriksson & Kovalainen, 2015). Subjectivist ontology suggests that reality is created through people's perceptions and experiences, which can vary between time, context and person, acknowledging that multiple realities can exist (Eriksson & Kovalainen, 2015; Saunders et al., 2023). According to the subjective epistemological view, the external world outside our observations and interpretations is not possible (Eriksson & Kovalainen, 2015).

The interpretivist approach supports the aim of this thesis, which is to explore the impact of AI adoption on the future of the audit profession in international auditing firms, prioritising the depth of findings instead of generalisability (Eriksson & Kovalainen, 2008). However, it is good to acknowledge that the axiological view highlights that the researcher's interpretations of the data, including their beliefs and values, affect the research process (Saunders et al., 2023). Therefore, this study aims to increase transparency by providing detailed information on the data collection and analysis processes.

Research purpose can be categorised as purposive, descriptive, exploratory, evaluative, explanatory, or a combination of these (Saunders et al., 2023). This thesis adopts an exploratory research approach as the research topic has not yet been sufficiently researched, and the field is constantly transforming due to fast technical developments. The research questions are formulated as "how" questions to gain deeper insight into the phenomenon, aligning with exploratory research (Saunders et al., 2023).

Research designs can be categorised into quantitative, qualitative, or mixed methods based on the type of data collected (Saunders et al., 2023). This study uses non-numeric data to answer the research questions (Bryman, 2012) making the research design of this study qualitative. A qualitative approach was chosen because it best supports the exploratory purpose of the study, as it allows for gathering detailed and rich data of interviewees' perceptions and experiences through the interview data collection method (Moser & Korstjens, 2017). More specifically, the thesis uses a single data collection method, which is interviews, and therefore the study is considered a qualitative, mono-method research (Saunders et al., 2023).

This study follows a case study approach commonly used in exploratory research (Yin, 2018). A case study allows for an in-depth understanding of a topic in its real-life context instead of a controlled environment (Yin, 2018), which supports this study's exploratory nature. Case studies can explore, for example, organisations, groups, individuals, associations, events or processes, and they can be conducted as a single case or a multiple case study (Saunders et al., 2023). This thesis adopts a multiple case study approach, examining auditing executives from different companies to gain an understanding of different contexts. The time horizon of this thesis is cross-sectional as it explores the topic at a specific time instead of observing it over an extended period (Saunders et al., 2023)Consequently, this study does not aim to provide an overview of AI's long-term effects on the auditor's role but instead to offer a view of AI's current and expected effects on the auditor's role while acknowledging the rapid changes within the field.

5.2 Data collection and sample

This thesis's data collection was conducted through semi-structured interviews. Semi-structured interviews are guided by pre-determined themes, topics, or issues, but each interview's wording and question order can be modified (Eriksson & Kovalainen, 2015). This interview structure allows the interviewer to ask follow-up questions when needed, and for different topics to arise during the interview, which helps collect rich and detailed data (Saunders et al., 2023). This makes semi-structured interviews effective for gaining a deeper understanding of a phenomenon, which supports this thesis's exploratory nature (Saunders et al., 2023). However, some challenges linked to semi-structured interviews should be addressed. While semi-structured interviews allow for more in-depth discussion, it is also important to remember that the data can be affected by the interviewer’s way of interacting and asking questions during the interview (Saunders et al., 2023). Also, the interviewer should find a way to address all predetermined topics without following the interview questions too strictly, as that can prevent the interviewee from bringing up important topics (Eriksson & Kovalainen, 2015).

The interview questions (see Appendix 1) were created based on the theoretical framework (see Figure 7). The interview questions were divided into four sections: background and professional experience, AI use in auditing, benefits and challenges of AI in auditing, and the future of auditing with AI. The semi-structured interview guide was tested through a pilot interview, and the questions were improved based on that. The questions were used as a guide during the interview to ensure all topics were discussed. However, the questions' formatting and order were slightly changed based on the discussion. The interview questions were provided to interviewees in advance to help them prepare for the interview, and the thesis topic was also presented briefly at the beginning of the interview.

The interviews took place in February and March 2025. Synchronous electronic interviews were conducted in real-time in Microsoft Teams (Saunders et al., 2023). The interviewees were interviewed one-to-one, so each interviewee was interviewed separately

(Saunders et al., 2023). 8 out of 9 interviews were automatically recorded and transcribed in Microsoft Teams with the interviewee's permission, allowing the interviewer to concentrate on listening and questioning (Saunders et al., 2023). The interviewer also made short notes during the interview to provide backup and help remember what was said to avoid asking for something that had already been answered. The author then corrected the transcriptions based on the recordings. One interview was not recorded due to company policy, meaning that the interviewer only made notes during that interview. One interview was conducted in English, as it was the interviewee's native language. The rest of the interviews were conducted in Finnish, the native language of both the interviewer and interviewee, to minimise the risk of misunderstandings due to language barriers. The interview extracts used in the findings were carefully translated from Finnish to English, maintaining the original meaning and style (Saunders et al., 2023). The extracts were also polished to enhance clarity, which was requested by the interviewees. However, this has been done without altering the original meaning of the extract by, for example, removing repeated and filler words.

This study used non-probability sampling as it best fit the study's aim of understanding a phenomenon instead of creating statistical data (Saunders et al., 2023). This study focuses on the impact of AI automation and augmentation on the auditor's role in international auditing firms in Finland. The target population originally consisted of auditing executives from international audit firms operating in Finland, but it later expanded to include executives working closely in audit technology development. This target population was selected to gain a broad understanding of both the adoption and development of AI technologies in audit firms and the resulting changes to auditors' roles. International auditing firms were selected because they are likely to be further along with AI adoption due to better resources.

Both purposive sampling and snowball sampling were used to create the sample. Purposive sampling was applied by searching international audit companies' websites and LinkedIn to find audit executives in Finland. Suitable candidates were then contacted via email. A few participants were also contacted through personal networks. In snowball sampling, the researcher finds additional subjects through initial contact with people relevant to the research topic (Bryman, 2012). Some interviewees were found through snowball sampling, as a few were recommended by an interviewee or an initial contact who did not participate. This also led to the expansion of the target population, as some auditors recommended interviewing someone from their IT team working on audit technology development. Including a few audit technology specialists made the data more diverse.

The overview of the interviewees is presented below (see Table 2). The sample consisted of nine interviewees from six different companies. The sample included both men and women in executive positions in auditing, with a few interviewees focused on the technological development of auditing. The interviewees' field experience from auditing or IT varied from five years to over thirty years. The interviewees were from the following international auditing companies: EY, Deloitte, KPMG, PwC, Grant Thornton and BDO. This sample provided varied insights on the topic from multiple perspectives. The duration of interviews varied between 29 and 57 minutes.

Table 2. Overview of interviewees.

Interviewee	Code	Company	Duration
1	1A	A	32:34
2	2B	B	29:16
3	3C	C	56:32
4	4D	D	57:00
5	5E	E	44:34
6	6A	A	48:58
7	7D	D	30:57
8	8F	F	30:26
9	9B	B	45:47

5.3 Data analysis

This thesis adopts a primarily inductive approach to analyse the collected data. However, even though it does not create a hypothesis to test existing theory, it incorporates some deductive elements as the theoretical framework guides data collection and analysis (Saunders et al., 2023). Inductive research develops a theory based on collected data, whereas deductive research tests existing theories through data analysis (Bhattacherjee, 2012).

This thesis uses thematic analysis, which is a widely used technique in qualitative research (Bryman, 2012). Thematic analysis uses coding to identify themes and patterns from the data by analysing it during and after data collection (Braun & Clarke, 2006). Since this study primarily adopts an inductive approach, the themes emerge from the data instead of being predetermined based on existing theory (Naeem et al., 2023). The analysis followed the six-step thematic analysis process suggested by Saunders et al. (2023). First, the data was familiarised by checking transcripts, which involved watching the recordings and reading the transcripts. Then, the data was coded by categorising data units based on their meanings. The codes were modified during the analysis, and new codes were created based on the data. After the data was coded, the codes were grouped into broader categories, which were then developed into themes. Finally, after developing the themes, they were defined, refined and named to reflect their relevance to the research questions. The five themes that emerged from the interview data are (1) current use of AI in auditing, (2) perceived and potential benefits of AI, (3) challenges and risks of AI use, (4) transformation of the auditor’s role, and (5) future skills and competences.

5.4 Reliability and validity

Reliability and validity are most used in quantitative research to assess the quality of the research (Saunders et al., 2023). However, their applicability to qualitative research has been questioned (Bryman, 2012; Eriksson & Kovalainen, 2015; Saunders et al., 2023). If a study adopts subjectivist ontology and epistemology, Eriksson and Kovalainen (2015) suggest replacing the traditional validity and reliability assessment with the evaluation of trustworthiness by Lincoln and Guba (1985). Therefore, this research's quality will be assessed based on trustworthiness, which consists of credibility, transferability, dependability, and confirmability.

Credibility is similar to internal validity in quantitative research (Saunders et al., 2023). It measures whether the findings accurately represent the participants' experiences (Eriksson & Kovalainen, 2015). Member validation was used to increase the credibility of this research (Saunders et al., 2023). The interviews were recorded and transcribed on Microsoft Teams, so participants could immediately see the transcript. After analysing the data, participants received the interview extracts to ensure everything was understood as they intended. Credibility could also be increased by using multiple data sources or spending a prolonged time with participants (Ahmed, 2024), which were not implemented due to the restricted nature of this master's thesis.

Transferability can be referred to as external validity or generalisability (Bryman, 2012), as it refers to the degree to which the research findings can be applied in other settings (Ahmed, 2024). Qualitative research is usually conducted on a small sample, and therefore it is more commonly used to explore a specific phenomenon instead of generating statistically generalisable results (Saunders et al., 2023), which this study does. The research context, methods and sampling process were described in detail to increase transferability and allow other researchers to evaluate the applicability of the study to their situation (Ahmed, 2024).

Dependability is the qualitative equivalent to reliability in quantitative research (Bryman, 2012). It measures how well the research process has been documented to the reader (Eriksson & Kovalainen, 2015). The process of data collection and analysis has been recorded to increase transparency and replicability (Ahmed, 2024). This study followed the six-step thematic analysis process by Saunders et al. (2023), which helps the reader to understand how the analysis has been conducted, increasing dependability.

Confirmability in qualitative research can be referred to as objectivity in quantitative research (Bryman, 2012). It measures the impartiality of the findings, ensuring that they are not affected by the researchers' biases (Kakar et al., 2023). Potential researcher biases in qualitative research are acknowledged, and objectivity is sought throughout the research process. The confirmability of the study was increased through member checking, meaning that the interview extracts were sent to participants for validation to avoid misinterpretation (Ahmed, 2024). In addition, the translation of interview extracts was done carefully to retain the original meaning.

6 Findings

This chapter presents the relevant findings of the research. This study aims to explore the impact of AI automation and augmentation on the role of auditors in international auditing companies. This chapter's structure is based on the five themes that emerged from the interview data. First, the current application of AI in auditing is discussed. Then, the benefits and challenges of AI use in auditing are presented. Finally, the transformation of the auditor’s role due to the use of AI in auditing is elaborated, and the future skills and competences are presented.

6.1 Current use of artificial intelligence in auditing

To understand how AI will affect the auditor’s role, it is essential to examine how AI is currently being used in international auditing firms. To determine the extent to which AI is currently utilised in international auditing firms, participants were first asked whether their firm uses AI in auditing. This included generative AI and traditional auditing technologies such as machine learning, natural language processing, computer vision, and expert systems.

Many interviewees stated that AI is not yet widely used in auditing companies. One interviewee stated that, regardless of the audit company, the use of AI is still in its early stages, and another mentioned that AI tools are not used directly in auditing but are being developed. Most interviewees mentioned that AI cannot currently be used in audit procedures due to regulatory uncertainty. One interviewee stated that due to strict rules on AI use, it cannot be used in client work.

> *It [artificial intelligence] is starting to be used, but it is still in its early stages for all. Whatever the company, it is still in its early stages in auditing. (1A)*

> *Well, maybe we do not use AI tools directly in auditing at the moment, but they are, of course, under development. (3C)*

At the moment, there are quite strict rules about what AI can be used for, referred to as business rules, so we cannot use it [AI] directly in customer work. (6A)

However, many interviewees reported using traditional AI technologies, such as machine learning, natural language processing, or computer vision, in various tasks during their audits. The tasks mentioned included handling invoice information, comparing financial statements, identifying outliers in data, creating samples, and conducting a client background check.

You can enter this year's financial statement and last year's financial statement, and it checks all the reference years automatically and marks the sections it was unable to match, so it really speeds up [the process]...but it may not be considered GenAI. (4D)

Yes, we have, for example, natural language processing and computer vision applications ... [the applications] can automatically combine invoice information and find the invoice amount and date from PDF documents, so they do not have to be browsed manually anymore, and then we have… this kind of tool developed for tick and tie of financial statements. (9B)

It became clear that the use of GenAI in auditing is at a very early stage. Although all interviewees reported some use of GenAI in their work, it is still limited to supporting tasks in most companies. One interviewee stated that GenAI currently does not perform actual audit procedures, so it is used mainly for assisting tasks. According to the interviewees, GenAI improves the auditor's work by performing administrative tasks such as text processing, translation, information retrieval, and document review.

You can use it mainly for managing your work. (hidden word) [GenAI application] is good for making summaries from daily emails, or it can draft you an email or search for something. (6A)

So what (hidden word) [GenAI application] is basically used for at the moment is the acquisition of information or assistance or such, so it does not yet do actual audit procedures. (9B)

Everything from how we write our proposals for new work, it [AI] can help us create a narrative story for the slide deck or the proposal we are preparing. (7D)

The interviewees were also asked if there are tasks that AI has automated or if there are tasks where AI assists auditors in their work. Most respondents agreed that AI has not yet automated audit tasks. Some respondents mentioned that while AI has not been used for automation, they have automated many procedures with other technologies, such as RPA. One interviewee stated that they use robotics and data analytics for automation, but does not believe that using AI for automating is yet possible in auditing. However, a few respondents mentioned that document comparison has been automated with traditional AI technologies.

> *Everything, at least, on the audit side still requires specialists, so no work step is completely done by AI. (4D)*
>
> *Not at this moment directly [automated] with Chat GPT or any other similar. (3C)*
>
> *We have automated very much through robotics and analytics tools but to actually add some AI on top, that we have not done. I do not think anyone has actually done that yet. (6A)*
>
> *It [financial statement comparison] can also be automated quite far, so that the machine does it. (4D)*

The reported extent and nature of AI use varied between firms and between individuals within the same organisation. This could be due to differences in AI knowledge and attitudes towards AI. Over half of the interviewees mentioned difficulty categorising AI or distinguishing it from other technologies, and one participant also highlighted their limited understanding of the underlying technologies behind the technological applications. Another finding that can explain the differing answers of employees in the same firm is that some interviewees mentioned that the use of AI technologies can vary in the organisation between individuals.

> *I had to check these categories, because I do not have so much theoretical information in the background. (9B)*

> *I do not know if it goes under artificial intelligence. I notice that I do not even know all the categories correctly…How much [artificial intelligence] is used depends much on the audit firm and the auditors. (4D)*

> *I might not know how our technology in the background has actually been working…I know we have automation, but I will not directly say how much AI is involved in that. (2B)*

There was variation in interviewees' answers regarding how long AI technology has been used. Some stated that traditional AI tools had been used for several years, and GenAI was adopted more recently in 2024. However, many interviewees were uncertain about the exact adoption timelines for different types of AI technologies or referred to all types of AI at once.

> *GenAI has been around for a year or something like that...and the OCR has probably been around for 4 years or something like that. Therefore, OCR could be classified as a basic application in that sense. (1A)*

> *It [GenAI] is not an old thing, officially we have had it since probably 2024, when this (hidden word) [GenAI application] came. (3C)*

> *I must say that I might not remember exactly, 2-3 years maybe. (2B)*

There were differences in the type of Generative AI companies used. Some used public or third-party applications, such as Copilot or ChatGPT, while others had developed similar tools within their organisations in a secure environment. Many interviewees highlighted that client data cannot be entered into public AI tools to ensure data security and confidentiality. Some interviewees even stated that public AI tools are forbidden entirely. One interviewee expressed that AI tools should be internal for data confidentiality reasons.

> *If we think about examples, then something we must always think about is that we cannot use any public tools, services or programs. So, ChatGPT, for example, is completely prohibited because we cannot trust the customer's [information into the*

public tool], and in auditing, of course, we have to think about the confidentiality of information. (4D)

The tool should be only for our use, because of regulations such as GDPR and confidentiality. We cannot enter any documents in public services. (5E)

Most interviewees were optimistic about the development of AI in auditing and believed that significant developments would occur very soon. A few interviewees had a more sceptical outlook on AI and did not expect fast development, but they still agreed that changes were coming.

Now we should still come up with the AI side on top of it [current technology], so that we can actually do it…maybe we have learned a little more and are better at this, so maybe it will not take 10 years, maybe it will take only 3 years or 5 years. I do not know. Hopefully, learning it will not take longer than that, but it is a really painful and long road. (6A)

This year the development [of AI] will probably be quite fast. (3C)

This [AI] is something that develops, and what it is today may be completely different next year, so it is going forward at a fast pace, and there will definitely be interesting times ahead in the future. (2B)

Nearly all interviewees stated that their companies are actively seeking ways to implement AI more fully into the audit process. Some mentioned that their companies have made significant investments in the development of AI. Interviewees reported trying to increase efficiency, improve quality and find ways to have AI replace some tasks.

Large sums of money are being put into this because we see a lot of potential here, but… there is still a long way before this thing actually goes nicely. (6A)

We are constantly thinking about how this AI, and all, can make auditing more efficient and improve the quality of the audits and therefore also improve the quality of financial statements. (3C)

We are sort of considering these different applications, like how it [AI] could be used efficiently, so that we could even replace some procedures with it, but it is challenging. (5E)

In conclusion, the use of AI in auditing is still in its early stages. Interviewees reported that AI cannot be used in audit procedures yet. While traditional AI has been used in many companies for several years, GenAI has only recently been implemented in auditing companies. Traditional AI is used for routine tasks such as comparing financial statements and matching invoice information. The use of GenAI is mainly limited to administrative tasks such as text processing and information retrieval, at the moment. Most interviewees stated that no audit procedures have been automated yet. However, most interviewees had optimistic views on AI and believed it would develop rapidly.

6.2 Benefits of artificial intelligence in auditing

The interviewees were asked whether AI use had brought any benefits and what kind of benefits they believed AI could bring in the future. The answers regarding perceived and potential benefits varied, mainly because some interviewees had not yet experienced benefits due to differing levels of AI use. Those who reported perceived benefits also reported using AI more extensively than those who reported potential benefits. However, the mentioned potential benefits were similar to the perceived ones, indicating that interviewees had similar views on the benefits that AI use in auditing has brought or could bring in the future.

Most of the interviewees mentioned increased efficiency, as well as reduced time and effort, as perceived and potential benefits. A few interviewees stated that AI's time-saving benefits have and could reduce the auditors’ workload, resulting in less evening and weekend work.

> *Well, at least from a personal experience, I can say that efficiency and time savings have come [from AI use]. (9B)*
>
> *It would save human labour if we would develop it [AI] to replace the basic work. (5E)*

And it is not necessarily always the savings in manpower, but it makes this work more enjoyable, so that we would not have to work under time pressure...sometimes we have to work evenings and weekends, so we have also been able to reduce people's workload. (4D)

Another benefit perceived by two interviewees from the same organisation and seen as potential by one interviewee is improved work experience, which is also linked to reduced workload. One interviewee explained that the auditor’s work experience is improved when AI tools do the mundane, routine tasks, and another stated that AI use allows the use of people’s full capacity, leading to benefits for the company and employees.

We get to automate these manual tasks and get benefits there, while on the other hand when we get machines to do these manuals [tasks] it is making the work more enjoyable. (4D)

[AI use improves] the experience of our people. It benefits the people and the business, because then you are using people to their maximum capability to actually do what they are capable of. (7D)

The majority of interviewees also stated improved quality and consistency as either a perceived or potential benefit. A few interviewees elaborated that AI has improved the quality of audits by increasing uniformity and reducing human error.

One benefit we have is the quality, the uniformity, as the machine always does things the same way and is always as alert. (4D)

For example, these basic typing errors people make, when they look at the numbers and then they may have marked that it matches, even though it has not actually matched. So, these kinds of things cannot happen if a bot does it, as it determines precisely whether it matches or not. (9B)

A few interviewees also mentioned that AI could assist in risk detection. One interviewee stated that AI could detect anomalies and create suggestions for appropriate risk procedures, and another brought up AI’s ability to identify signs better than humans.

AI can support or assist, for example, noticing anomalies, making suggestions for the inspection strategy, making suggestions for risks and procedures to tackle these risks and such. (9B)

Somehow, the risk analysis is something where a model like that [AI] can see more things than you. (1A)

In summary, interviewees reported multiple perceived and potential benefits of AI use in auditing (see Table 3). The most significant benefits were increased efficiency, enhanced quality, better work experience, and improved risk detection.

Table 3. Perceived and potential benefits by the interviewees.

Benefit	Perceived	Potential	Total
Increased efficiency	II	IIII	6
Enhanced consistency & quality	III	III	6
Improved work experience	II	I	3
Improved risk detection	I	II	3

6.3 Challenges of artificial intelligence in auditing

The interviewees were asked whether they had experienced any challenges from AI use and what kind of challenges they could see coming in the future. While interviewees mentioned multiple benefits of AI use, they also had many concerns regarding its use (see Table 4). Interviewees also considered many of these challenges barriers to AI implementation.

The lack of transparency in AI systems was a big challenge for many interviewees. The interviewees mentioned that the problem is that AI does not tell how the answer was generated, which means that it cannot be verified. One interviewee also mentioned that the reasoning behind procedures should be documented in the working papers, and another noted that AI results are not replicable because it can give a different answer every time, even with the same prompt. A few interviewees also mentioned that for AI output to be usable in auditing, AI should at least tell how the conclusion was made.

> *The problem is that it does not leave any trace of what really happened, the output just came from there...so if you need to be able to repeat what has been done in the audit, well each GenAI output is practically a different thing it might not give the same result even with the same prompt. It [GenAI] is just a black box where things came out. (1A)*

> *We must be able to present them [the justifications] in the working papers, and these documentations must have them, the justification of how it has come [to this conclusion]. (3C)*

> *Of course it should at least tell how it [the answer] has been done, so that we can be sure of it. We cannot take the answer without understanding the parameters and how it has ended up in the conclusion. (5E)*

A perceived challenge mentioned by nearly all interviewees was a lack of trust in AI output, which is closely related to the previous challenge, the lack of transparency of AI systems. Interviewees explained that they cannot trust AI-generated results because they do not know where the information came from.

> *But you cannot really trust that it is for sure 100% correct...We do not know where it [AI] has gotten the information from, it could be completely wrong in the end…Well, of course, the challenge is that you can actually trust it, how can we make sure that the output that comes from there is correct so that we can somehow verify it. (6A)*

> *Thus far, we cannot yet sort of trust the result...so at the moment AI gives hints and answers, but they are not necessarily always reliable. (5E)*

Another challenge that came up in most of the interviews is that AI use requires data standardisation. Interviewees mentioned that for AI or RPA to process information, the base data must be standardised. Many also stated that the lack of standardisation across client systems can create challenges because manually editing client data for AI or robotic use requires significant time.

To be able to use it [automation], the customer's processes must be standardised, and things have to be done in a certain way. If they do not do that, then robotics or automation is a waste of time because it does not work. (6A)

Every time we use automation, we have to manually map the customer data before we can utilise automation. It is very time-consuming, and we have to do it for every single customer, and we cannot do it for small customers because it would never pay itself back. (4D)

Another challenge is perhaps standardisation, which, in my opinion, should have been in a better state many years ago than where it is now... But, it has to be understood that it [standardisation] is the first step to being able to automate or input working papers into AI. So, they must be in a certain format so they can be processed, and that will still take some time...first we must, of course, standardise our working papers and methods before they can be automated or filled with AI. (9B)

Many interviewees noted that AI cannot yet be used to create audit evidence due to regulatory uncertainty and transparency concerns. The most significant barriers to AI adoption in audit procedures were regulatory concerns, particularly regarding International Standards on Auditing (ISA) and other regulatory bodies, such as the Finnish Patent and Registration Office (PRH). Many interviewees stated that they cannot use AI in audit procedures because regulatory bodies have not yet acknowledged AI use in their regulations. One interviewee brought up a reciprocal situation regarding the regulations. They explained that the regulation issue is two-sided, as both the regulators and auditing companies are waiting for the other to make a move.

In auditing, you can use it [AI] to assist. You are not allowed to use it in a way that, for example, GenAI would do something entirely, considering ISA standards and others. I think that the problem is that it does not leave a trace of what really happened, the output just came from there. (1A)

I do not think that anyone, or if someone uses [AI], I would dare to challenge a bit, because I believe that at the moment, you just cannot or are not allowed to use it [AI] even. The supervisor, who supervises auditors, the PRH [Finnish Patent and Registration Office] and auditing standards, such as the ISA standards, do not acknowledge AI, they have not taken it into account. (6A)

I feel there is a bit of like an egg and chicken problem, as the regulators may be waiting for auditing firms to start doing these things [applying AI], and then the auditing firms may be waiting cautiously and will not start doing anything as the regulator has not taken a position on these topics yet. So, they [auditing firms] do not dare to go to the forefront to do things, so both parties are waiting for the other to make the initiative. (9B)

Many interviewees mentioned the risk of overreliance on AI when AI use increases. Interviewees described the risk as humans relying on AI too much. One interviewee brought up the challenge of balancing how much to rely on AI. Some interviewees also raised concerns about how future auditors will learn if AI does the work.

Well, I see the risk right there that people rely too much on AI. (3C)

The challenge for all of us is how much do we rely on AI and where does the boundary lie. (7D)

If AI does everything, how does real learning happen, because learning happens by doing. (8F)

A few interviewees mentioned resistance to adopting new tools as a challenge. They stated that new technology tools are difficult to implement if human auditors are unwilling to learn to use them, and that people can have difficulties implementing new things and outlearning old habits.

The challenges are probably the skill development. It is an opportunity, but it is also a challenge, as, of course, it is always unpleasant to outlearn old ways of doing things before being able to learn something new. Also, some people get excited about things, about technology, more easily than others. (4D)

I think, first of all, that people should try and learn to use [AI]. It is so difficult for people to start using new things...people do not always want to, have not been able to, or have not been bothered to. So that is, in my opinion, the biggest challenge. (6A)

Most respondents also mentioned concerns about data security and confidentiality. However, they did not describe it necessarily as a challenge but as something that has to be considered to avoid challenges. Also, it was mentioned that the AI model should be trained with client data, which is not allowed without client permission.

> *I do not know if these are actual challenges or if these are just things that must be thought about in the process in general. However, everything like vulnerability, data security and then of course the integration into our existing systems...we should train the model with our customer data, of course, but we are not allowed to do that, we have to ask every customer now whether we get permission to train our AI model, so that process is quite slow. (9B)*

Interviewees mentioned multiple challenges AI can bring to auditing (see Table 4). Most of the challenges were currently perceived, with one potential future challenge. Many of the challenges were also described as barriers to AI use in the audit process. The most significant challenges discussed in the interviews are a lack of trust in AI output, the need for data standardisation, overreliance on AI, a lack of transparency and regulatory uncertainty. The importance of data security in avoiding challenges also came up in most interviews, even though it was not necessarily seen as a challenge. A few interviewees also mentioned the resistance to adopting new tools as a significant challenge.

Table 4. Perceived and potential challenges by the interviewees.

Challenge	Perceived	Potential	Total
Lack of trust in AI output	IIIIIII		7
AI use requires data standardisation	IIIIIII		7
Data security and confidentiality concerns	IIIIII		6
Risk of overreliance	I	IIII	5
Lack of transparency	IIIII		5
Regulatory uncertainty	IIIII		5
Resistance to adopting new tools	II		2

6.4 The transformation of the auditor’s role

This chapter presents the interviewees' views on how AI will affect the future role of auditors. The interviewees were questioned about their views on auditors' future role and skill requirements, the potential of new job roles emerging, the future relationship between auditors and AI, and AI’s effect on auditor employment.

This chapter's structure follows the themes that emerged from the interview data. First, the relationship between AI and auditors, AI’s impact on auditor employment, and changes to the auditor’s role are examined. Then, views on auditors’ future competences are presented.

6.4.1 The role of AI in auditing and its impact on the auditor’s role

Nearly all interviewees stated that AI cannot entirely replace auditors, at least in the foreseeable future. However, all agreed that AI can support auditors' work now or in the future. Interviewees identified that some elements, such as social interaction and professional judgement, cannot be replaced by AI. One interviewee also stated that the use of AI requires a person.

> *I would say that people will still be needed to do the review work and certain types of complex interpretations. I am not saying that artificial intelligence could not do them even better, but these are the areas that will remain at least for the time being. (2B)*
>
> *Will not replace completely, but they will become auditor’s friend, a teammate...You cannot do an audit unless you meet and interview people…We also need to assess what people say and what happens outside of bookkeeping that would not have been recorded, for example. So, we still fortunately have the kind of social side of people and discussion with customers, and the understanding of business and how things are related to each other, which means that we are talking about professional judgement and understanding of business. So, it is difficult to think that artificial intelligence could replace those two at the moment. (4D)*
>
> *Well, I think that it [AI] will not replace. It [AI] will assist, yes, but not replace. (3C)*

Well, it [AI] will not replace…as I explained it must get the right things written in the prompt and thought about how things are done, which requires a person. (6A)

While interviewees agreed that AI will not completely replace human auditors, some believed that the number of auditors could be reduced in the future. The interviewees' opinions about the future employment of auditors were divided. Approximately half of the interviewees believed that the number of auditors could potentially decrease, especially at the entry level, as AI will most likely replace the tasks they have traditionally performed. In contrast, the other half did not expect the number of auditors to decrease, with a few stating that it might even increase. Some explained that the number of auditors will likely not decrease because increased verification demands from customers, regulators, and investors can increase audit procedures.

Yes, it will probably reduce the number of employees in the field, but it does not remove. As long as the audit is in this form, someone has to make the conclusion eventually...However, that can of course be a threat to the basic auditor, such as assistants, as they do not yet have the experience and other, so artificial intelligence can replace the basic auditors' or assistants' work in a way. (5E)

The number of auditors in the traditional sense of what is included in the job duties, will for sure decrease, but on the other hand when the client's system environment advances, the nature of our work changes. So, what we verify actually increases. However, there will probably be less need if we consider the traditional task that it [auditing] has been before or what it is today. Nevertheless, in fact, this change only brings us new territory. (4D)

This has already been discussed during the technological revolution, that the number of auditors would decrease. However, the faster the regulation will tighten, the number of companies will increase, the need for verification will increase, so I disagree that the number of auditors would decrease, because perhaps the work will just change its form. (9B)

One interviewee believed that the number of auditors could increase in the future for two reasons. First, they mentioned that job opportunities can increase as AI expands the scope of auditing. Second, they noted that AI can improve human auditors' performance, increasing their value and encouraging companies to retain them.

AI accelerates the person and allows them to do more valuable work, right? So, then each individual team member becomes more valuable because they are both using their own brain power more. But they also have AI there to accelerate what they are doing, so each individual person is more valuable. So, to me, that means you would want to retain those people. Then, the type of work we can do can also expand. I think auditing will evolve, and the regulators, investors, and everyone who rely on or trust auditors would also like auditors to do more. People are pushing for it, and the thing that stops it is time, cost and everything. If we could offer that and broaden what we do, I think investors and regulators would also want that. So, I think that is why you end up with more auditors and not fewer. (7D)

Multiple other interviewees also believe that AI can create new opportunities for auditing by creating new roles and expanding the auditing service offering. Many interviewees believe that AI will create new jobs in auditing, and some stated that new roles in AI audit development have already been established in their companies. A few interviewees mentioned that auditing could expand towards more consultative services, while stating that auditors cannot offer direct advisory services. One interviewee also brought up the possibility that auditing could become an ongoing process that gives constant confirmation instead of being a yearly report.

New job descriptions, tasks and roles will certainly arise with 100% certainty...this automation and robotics have created. We have many people who are called (hidden word), who in practice no longer do client work, they have previously done auditing but have moved to development to do these kinds of system development things and robotics. (6A)

In the future, auditors' deep understanding of industries, technologies, customers and different accounting questions will perhaps shift more towards discussing form with the customer. Even though auditors cannot provide direct advisory-style services, this consultative side will still increase. (9B)

In the future, we may go more towards the kind of [auditing], where instead of happening once a year, we will have some monitors on all the time, and when there are anomalies, they are analysed…it can entirely change this so-called auditing, where it would not be a report that is issued once a year, but instead something that it is valid all the time. (4D)

Many interviewees described the future relationship between human auditors and AI as collaborative. Some mentioned that the team structure has changed as AI has been implemented into audit teams alongside traditional human colleagues. Many interviewees perceived AI as a member of the audit team, a coworker, or an assistant. One interviewee highlighted the benefits of human-AI collaboration, stating that combining humans and AI creates much better results than either alone.

> *I think for me, it is that combination of a human expert plus AI together. The output is much higher quality than if it were just a human on its own, and definitely much higher quality than just the AI as well. You need both together. (7D)*

> *It is basically like a team member or an assistant. However, AI is not responsible for anything, so it is not AI that has done something. It may have suggested it, and then you yourself have gone through it and approved it. It is kind of like a general assistant taking care of this and that. (1A)*

> *Artificial intelligence has come to stay and will be like a colleague in the future…and the team and friends are different, as there are machines and there are specialists, and then there are those traditional colleagues…so the team structure has also changed. (4D)*

Regarding the future relationship between human auditors and AI and changes in auditors' responsibilities, many interviewees mentioned that the auditors' future role will likely involve supervising AI. Interviewees pointed out that the auditor will be essential in reviewing AI-generated results because responsibility cannot be given to AI. One interviewee stated that auditors must ensure that the information AI creates is correct and obeys the law, and another added that machines have to be verified and taken care of.

> *The auditor will be more in a supervisor role. In a way, making sure that the conclusions of artificial intelligence are correct and legal. (5E)*

> *At the same time, if we think of auditors, our work changes, because assurance is always needed. So, the machines do not work unless someone takes care of them and also verifies them a bit. (4D)*

> *Yes, it will support, and it is developing constantly...I perhaps see it so that the auditor is the leading actor, and AI is then like assisting. In my opinion, this comes from our auditing law, because the auditor's responsibility is pretty strictly defined, and this responsibility cannot be given to artificial intelligence. (3C)*

Another common change to the auditors' role mentioned by many interviewees was that, as AI will replace manual routine tasks, auditors' work will become more analytical and adaptable. A few interviewees also mentioned that this shift could result in auditors focusing more on strategic decision-making and client relationships.

> *For sure, I mean it is clear that the work will become more applicable and basic work will be left out. (5E)*

> *So those kind of basic routine and manual tasks artificial intelligence will replace... the role of the auditor will perhaps change more to an expert role, where auditors focus on managing the customer relationship, customer service, communication, strategic decision making and then the so-called artificial intelligence would so more of the work, doing routine work and analysing data masses, processing, making work papers and such, so that could kind of be a relationship between these two. (9B)*

6.4.2 Future auditor competences

While many interviewees stated that some current auditor skills and competences will remain essential in the future, most agreed that the use of AI also requires auditors to develop new skills. Nearly all interviewees mentioned that technological skills and a willingness to use new technologies will be essential in the future. Some mentioned that auditors must know how to use AI technologies in their work, and others emphasised the importance of enthusiasm for learning and using the technology. One interviewee also stated that AI skills are important for differentiating in the future.

> *The work has become very different, and it requires different skills than before. (4D)*

> *You have to develop all the time and the systems are developing constantly. You have to learn to use new things and get educated. (6A)*

> *There has to be that enthusiasm and joy of learning and want to utilise that technology. In a certain way they have to be in balance. (4D)*

Those traditional values, for example, diligence or that you have a good number head, might not stand out as much in the future and instead, if people can take full advantage of artificial intelligence. (9B)

Many interviewees emphasised that core accounting knowledge will remain essential as AI use in auditing increases. They highlighted that auditors must still understand basic accounting principles such as double-entry bookkeeping and different regulations. A few interviewees mentioned that strong knowledge is important for evaluating and challenging AI's output and noticing irregularities.

The strong knowledge is kind of emphasised, so that if artificial intelligence would do those procedures, you could then even challenge its results and make the final decision yourself. Yes, the [most important] is gaining a broad knowledge and experience. And a broad knowledge of different regulations. (5E)

You still need to have an understanding of the basic stuff…I do not believe that accounting debits and credits will change even if artificial intelligence would come, but still bookkeeping will remain double-entry. And what will remain [important] is that you understand basic bookkeeping, because if you do not understand that, you cannot see the illogicalities in the background. (2B)

It is perhaps good to remember the basic pillars, as they must be in check....the basic bookkeeping, debit credit courses and the basic pillars can easily be forgotten. I would still remind all enthusiasts that even as artificial intelligence can tell you which way the debit and credit go, you still need to understand the basic things about bookkeeping and auditing, so that is always the number one priority. (9B)

Many interviewees also mentioned the importance of social and collaboration skills. Some also mentioned the importance of learning customer service skills and working as part of a team.

Well, on the other hand, you need to have social skills…because you cannot survive without them. (4D)

For example social [skills]. You have to learn to work with a team, you have to accept that you are part of a team. (6A)

This interaction and customer service skills are something that could be seen in practice. (9B)

Some interviewees also mentioned that analytical thinking will be important in the future. One highlighted that auditors should be able to adapt and use AI-created information, and another mentioned that different qualities in people will be needed in the future.

Our work becomes more technical all the time and this kind of analytical thinking is needed. So, what the machine produces must be able to be applied and utilised more and better. (4D)

Different kinds of qualities will be needed in people, such as analytical ability, and then probably people who can use and understand technology. So, the profile will change. (2B)

In summary, the interviewees believe that AI will not replace human auditors as human aspects such as professional judgement and social interaction remain essential. The views on whether AI will affect the number of auditors are divided. Some believe it could reduce the number, especially of entry-level auditors, while others believe that the number of auditors will not reduce or even increase. However, interviewees agree that AI will significantly change auditors' work by altering team structure, changing auditors' responsibilities, and potentially expanding audit services. Interviewees believe that as AI replaces manual tasks, auditors will focus more on analytical and adaptable tasks. Auditors' work will likely also involve supervising AI and reviewing its work. Interviewees also expressed that knowledge of core accounting principles, technological proficiency, analytical thinking, and social skills are the most relevant competences for succeeding in the future auditing environment.

7 Discussion

In this chapter, the study's findings are analysed and compared to existing literature to create a comprehensive understanding of AI’s effect on auditors' roles in international auditing firms. The structure of the discussion chapter is based on the themes that emerged in the findings. First, the current use of AI in auditing is discussed. Then, the benefits and challenges of AI use in auditing are examined. Finally, AI’s effect on the auditor’s role is analysed, and an updated theoretical framework is presented.

7.1 Current use of artificial intelligence in auditing

For analysing the effects of AI use on the role of auditors, as well as understanding the benefits and challenges, it is important to set the scene by presenting the current use of AI in auditing. The findings of this study support previous research on the current use of AI, highlighting the gap between potential and actual AI implementation.

The results show that overall, the use of AI in auditing is limited. Traditional AI is used in various tasks during the audit process, while generative AI is not used in audit processes and is mainly used in administrative tasks. Traditional AI tools such as machine learning, natural language processing and computer vision are used for invoice information combining, financial statement comparison, outlier detection, sample creation and conducting a client background check. These findings align with previous research, which shows that AI implementation is still at an early stage. Studies have reported the use of traditional AI, such as machine learning, natural language processing and OCR, for anomaly detection, document comparison and financial statement generation (Fedyk et al., 2022; Kokina et al., 2025; Samiolo et al., 2024). Similar to the findings of this study, Kokina et al. (2025) report that while traditional AI is used in auditing, the use of GenAI is still experimental. They state that GenAI has not yet been implemented into core audit procedures, which aligns with this study’s findings.

Most interviewees reported that AI cannot be used in audit procedures due to regulatory uncertainty and transparency concerns. While the interviewees did not explicitly define whether they were talking about traditional AI or GenAI, the findings imply that they were referring to GenAI, as multiple interviewees mentioned using traditional AI in audit procedures. Previous research has also identified the lack of regulation and transparency as challenges or barriers to AI use (Kokina et al., 2025; Seethamraju & Hecimovic, 2023), they were not directly addressed as barriers. These will be further discussed in the challenges chapter.

The results show some variation in the application of AI in auditing. Variations were identified between audit firms and even individuals within the same company. Some audit firms being further advanced in their AI use could explain the differences between companies. However, differences in defining and categorising AI could explain the variation between individuals from the same firm, as many interviewees expressed difficulty categorising AI. Another potential explanation for individual variation is how AI is applied within the firm, as many interviewees noted that individuals can affect how much they use AI. The individual's extent of AI use could also influence their overall knowledge of the firm’s AI applications. Research by Kokina et al. (2025) and Seethamraju and Hecimovic (2023) found differences in AI implementation between Big 4 and non-Big 4 companies, which partially supports this study’s findings by addressing differences in audit firms’ AI use. Previous research has addressed differences in AI use between audit firms but has not addressed differences between individuals from the same audit firm.

The findings indicate that although AI can automate specific manual tasks, AI mainly assists auditors. Therefore, even though automation and augmentation cannot be entirely separated, most current AI use can be considered augmentation instead of automation, based on the definition of automation and augmentation by Raisch and Krakowski (2021). While AI can automate certain parts of a task, the purpose of AI remains to assist the auditor by automating the manually heavy process and leaving the tasks that require human inspection to auditors. Another central finding is that interviewees stated that human auditors must always review AI-generated output, which supports the claim that most current AI use can be considered augmentation. These findings align with previous research by Kokina et al. (2025) and Munoko et al. (2020), which found that although AI has automated specific procedures, its current use in auditing is mostly assistive and thus represents augmentation rather than automation.

7.2 Benefits of artificial intelligence in auditing

The findings indicate that AI can bring multiple benefits for auditing firms. These benefits include both perceived and potential ones, as many of the interviewees had not yet experienced benefits due to limited AI use. However, the perceived and potential benefits were similar to each other. This aligns with existing research, as many previous studies mainly report potential benefits instead of perceived benefits due to the early stage of AI implementation in auditing (F. Y. Mpofu, 2023; Seethamraju & Hecimovic, 2023).

According to the results, efficiency is one of the most significant perceived and potential benefits AI automation can bring to auditing. Interviewees reported that AI's automation of routine tasks reduces the auditor's workload and saves time. These findings are consistent with previous research by Fedyk et al. (2022), F. Y. Mpofu (2023), Seethamraju and Hecimovic (2023) and Vitali and Giuliani (2024) which found that automating manual tasks saves time, thereby improving audit efficiency.

This study’s findings suggest that AI automation and augmentation can improve audit quality. Interviewees noted that quality improves when human error decreases because machines can perform tasks more consistently. This finding aligns with previous research by Vitali and Giuliani (2024) and F. Y. Mpofu (2023), which found that audit quality improvement comes primarily from AI automating routine tasks, as AI can perform many tasks faster and more accurately. Previous research by Fedyk et al. (2022) and Zhang (2019) found that audit quality can also be improved as automation frees human auditors' time and allows them to focus on more complex tasks. This study partly confirms the findings of Fedyk et al. (2022) and Zhang (2019), as the results show that the automation of routine tasks frees auditors' time, allowing them to concentrate on more challenging tasks. However, interviewees did not express an effect on audit quality, and therefore, this study cannot confirm that quality can also be improved through AI, freeing up auditors’ time. However, it could be assumed that when auditors have more time to focus on challenging tasks, it could positively affect audit quality.

Improved risk detection was considered a perceived and potential benefit. Interviewees mentioned that AI can assist auditors in risk detection by identifying anomalies and creating further suggestions for risk mitigation. These findings align with previous research by Bakumenko and Elragal (2022), F. Y. Mpofu (2023) and Vitali and Giuliani (2024), which found that AI can improve fraud detection by recognising anomalies from data and flagging them for human inspection. The improvements in risk detection can be considered to come from AI augmenting human intelligence, as both literature and the findings of this study recognise AI’s assistive role in risk detection and the important role of the human auditor who makes further judgements.

A novel finding of this study is that AI use in auditing may enhance auditors’ work experience. Two interviewees from the same firm mentioned that the most significant perceived benefit of AI use is improved work experience as AI automates manual tasks, allowing auditors to use more of their brain capacity and reach their full potential. Previous studies have not explicitly discussed this and, therefore, cannot confirm that AI automation improves auditors’ work experience. However, a related study by Cooper et al. (2022) researched accountants' perceptions of RPA and found that company executives believed RPA would improve job satisfaction, while lower-level employees did not report effects on work satisfaction. Therefore, the findings imply that AI automation may positively affect auditors’ work experience as it allows them to focus on more interesting and challenging tasks. However, due to the lack of supporting literature and a limited number of interviewees reporting improved work experience as a benefit, further research is needed to confirm this finding fully.

The findings suggest that the most significant perceived or potential automation-related benefits are increased efficiency, improved quality and better work experience. Meanwhile, the results imply that improved risk detection is related to augmentation.

7.3 Challenges of artificial intelligence in auditing

The findings show that AI can bring multiple benefits for auditing firms, but it can also pose challenges. Interviewees identified several perceived challenges associated with AI use in auditing, many of which were also considered barriers to AI use.

Based on the findings, a lack of trust in AI output and a lack of transparency are the most significant challenges regarding AI use in auditing. Interviewees reported that they do not trust AI-generated results, as the output cannot be verified, which was also considered a barrier to AI use. They explained that AI systems lack transparency as they do not provide insight into how the results were generated. These results are consistent with previous research by Munoko et al. (2020), Kokina et al. (2025) and F. Y. Mpofu (2023) which found that the lack of transparency of AI systems is a significant challenge that can decrease trust in AI-generated results. The findings also indicate that AI systems should be able to explain the process for auditors to use AI-generated results. This claim is supported by Seethamraju and Hecimovic (2023), who found that the effective use of AI would require AI outputs to be transparent. While not stated directly by the interviewees, previous research by Commerford et al. (2021) implies that auditors' distrust in AI technologies can cause them to dismiss AI evidence, which ultimately can negatively affect the quality and accuracy of audits. They highlight that auditors must trust in AI outputs to see benefits from AI use. These findings emphasise the importance of developing transparent AI systems to be able to effectively use AI in auditing.

Another major challenge of AI automation is that AI use requires data standardisation. Interviewees reported that the lack of standardisation in client systems creates challenges as the data has to be manually edited to be suitable for AI or RPA use, which can require a lot of time and resources. Some stated that, as standardisation requires significant resources, automation is not feasible for smaller clients as it would not be profitable. Previous research by Kokina and Davenport (2017) found that the lack of data consistency across clients is a significant barrier to AI implementation, which supports this study's findings. These results indicate that standardisation in the audit company and client firm is needed to save resources and facilitate more efficient AI use in auditing.

The results show that data security and confidentiality can include significant risks. Interviewees did not necessarily see them as a challenge but rather as something that must be considered to avoid challenges. These findings are aligned with F. Y. Mpofu (2023), who reported that using AI tools in auditing can compromise confidentiality. Another finding is that the training of AI models can be slow because AI models should be trained with client data, which requires careful consideration of data security and confidentiality. These findings align with Munoko et al. (2020) and Kokina et al. (2025) who highlighted the importance of ensuring client data privacy and the ethicality of AI model training. These findings imply that data security and confidentiality are not seen as direct challenges but as potential risk areas. The results suggest that increased caution should be practised when applying AI in auditing to avoid data security and confidentiality issues.

The results indicate that regulatory constraints pose a challenge to AI use and act as a barrier to AI implementation. Interviewees stated that AI cannot be used in audit procedures because current regulations, such as the ISA, have not yet acknowledged AI use. These findings are confirmed by Munoko et al. (2020) and Kokina et al. (2025) who found that the lack of regulations on AI use in auditing leaves auditing firms unsure of how AI can be used. One interviewee believes that the situation is reciprocal, as auditing firms are waiting for regulators to act, and regulators are waiting for auditing firms to use AI. Therefore, the findings suggest that the lack of regulation on AI use in auditing creates a challenge for audit firms.

Overreliance on AI is considered a potential challenge as AI use increases. Interviewees expressed concern about auditors placing too much trust in AI, especially during busy periods. Supporting views have been found by Anica-Popa et al. (2024), who stated that overreliance on AI could result in auditors disregarding their professional judgement, potentially affecting audit quality. Some interviewees also raised concerns about auditors losing learning opportunities if AI automates the work. This finding is supported by previous studies by Seethamraju and Hecimovic (2023) and Munoko et al. (2020) which considers the potential for beginner auditors to not acquire all necessary skills due to a deskilling effect from AI automating routine tasks.

Commerford et al. (2021) provide additional views by stating that there is also a risk of auditor under-reliance in addition to the concerns about over-reliance. Their findings showed that auditors are more likely to trust information from humans than AI, potentially leading to auditors dismissing evidence provided by AI. While the interviewees did not directly mention concerns about under-reliance, they did report a lack of trust in AI, which could have similar effects. As discussed earlier, a lack of trust can also limit auditors' effective use of AI. The findings suggest that both over- and under-reliance on AI can negatively affect auditing. According to the findings, overreliance could result in reduced audit quality and the potential deskilling of auditors, while underreliance or lack of trust could lead auditors to dismiss AI-generated information.

The findings suggest that auditors’ resistance to change can also be a challenge for audit companies. A few interviewees mentioned that auditors’ hesitance to adopt new tools is a significant challenge. While this challenge was not widely discussed in auditing-specific literature, a study by Abu Huson et al. (2024) supports these findings by identifying resistance to change as a challenge for implementing modern technologies in auditing. Therefore, the findings imply that resistance to change can hinder AI implementation. However, further research on the matter is needed due to the limited number of interviewees reporting this challenge and its limited discussion in audit-specific literature.

While interviewees reported most of the challenges mentioned in previous literature, they did not mention the challenge of algorithmic bias. The risk of AI delivering biased results due to prejudiced training data was discussed in previous research by Kokina et al. (2025), Seethamraju and Hecimovic (2023), and Munoko et al. (2020). This difference between literature and empirical results could be due to the reported limited use of AI in the interviewees' companies, which could mean that the risk of bias is not currently relevant.

The findings suggest that the most significant challenges of AI use in auditing are a lack of trust in AI output, AI's requirement for data standardisation, a lack of regulation, the risk of overreliance on AI, and a lack of transparency. Data security was not explicitly considered a challenge, but more as an area requiring special attention to avoid challenges. The study also found evidence that auditors' resistance to change could be a challenge for auditing firms.

7.4 The future role of auditors in an AI-driven workplace

The findings of this study suggest that AI will not replace human auditors, at least in the foreseeable future, but it will support auditors' work. These findings align with previous research by Dhamija and Bag (2020), Hasan (2022), Mackenzie (2025), Nguyen et al. (2024), Tiberius and Hirth (2019) and Vitali and Giuliani (2024), which agrees that AI will not replace auditors but instead assist auditors in their work. Based on the definitions of automation and augmentation by Raisch and Krakowski (2021), these findings suggest that AI will augment human auditors' capabilities instead of completely replacing auditors. The interviewees believe that some human elements, such as the social aspect of auditing or the professional judgement of human auditors, cannot be replaced by AI. This finding is also supported by previous literature, as studies by Mackenzie (2025), Hasan (2022), Nguyen et al. (2024) and Vitali and Giuliani (2024) believe that human elements such as professional judgement, creativity and professional scepticism cannot be replaced. Consequently, the findings of this study do not support the results of Frey and

Osborne (2017), who found auditing to be one of the most likely jobs to be replaced by computerisation.

While interviewees agreed that AI will not replace auditors, opinions on AI's effect on auditors' future employment were divided. Some interviewees believed that the number of auditors could decrease, while others believed that the number of auditors would not decrease or could even increase in the future. However, all interviewees stated that auditors will be needed in the future, and none of the interviewees expressed concern over the displacement of auditors. Approximately half of the interviewees expected that the number of auditors, especially entry-level auditors, could decrease in the future as they lack experience, and AI could automate tasks previously performed by them. This finding is consistent with previous research by Davenport and Miller (2022) and Fedyk et al. (2022) which found that the need for junior auditors can decrease due to increased AI use, noting that higher-level auditors are likely not affected. Conversely, the other half believed that the number of auditors would not decrease in the future because the use of AI in auditing can increase demands from stakeholders, resulting in more audit procedures. One interviewee expected that the number of auditors could even increase because AI can expand auditing, creating new job opportunities and making human auditors more valuable to the company by improving their performance. The findings of this study are consistent with the results of Law and Shen (2024), who found evidence that the use of AI can increase the number of auditors as AI use can create more job opportunities for auditors.

The findings of this study imply that human auditors and AI will coexist or, in some cases, already coexist in organisations. Interviewees reported changes in team structure where human auditors work alongside AI systems as AI has been implemented into teams. Several interviewees perceived AI as a team member, coworker or assistant, suggesting that AI is integrated with human auditors in the audit process. These findings support the concept of human-AI coexistence defined by Einola & Khoreva (2023, p.119) as "humans and AI in the workplace ecosystem as organisational members interacting with AI-solutions, including any kind of contact or bond between people and AI generating beliefs, attitudes, emotions, and behavioral patterns once the AI-solution is implemented and as it evolves over time." These findings also align with findings by Einola and Khoreva (2023), which suggests that organisations should expand to consider AI as a colleague to ensure successful coexistence. One interviewee also emphasised the need to integrate the capabilities of humans and AI to achieve optimal results, as they both enhance each other's abilities. This finding supports Raisch and Krakowski's (2021) views on successful coexistence as they define it as AI and employees augmenting each other's capabilities, allowing both to focus on their inherent strengths. Similar ideas have been presented within the auditing context. The findings of this study are also consistent with previous research by Gu et al. (2024), which introduced the co-piloted auditing model where auditors and AI collaborate to enhance auditors' capabilities. Based on its definition, co-piloted auditing can be considered very similar to coexistence (Einola & Khoreva, 2023) and augmentation (Raisch & Krakowski, 2021), but within an auditing context.

The anticipated changes to the auditor's role and the creation of new job roles can be considered further implications of coexistence. While the opinions on AI's effect on auditor employment differed, interviewees agreed that using AI will change auditors' work in the future and create new job roles. This finding aligns with Einola and Khoreva's (2023) idea that human-AI coexistence changes, creates and replaces human roles. This finding is further supported by previous research by Zhang et al. (2020), Libby and Witz (2020), Hasan (2022), Abu Huson et al. (2024) and Kokina et al. (2025), which found that the use of AI will transform the auditing process and the auditor's role and responsibilities. A main change that came up in the interviews is that as AI automates routine tasks, the auditors' role becomes more analytical and adaptable. Interviewees noted that automation allows them to focus on more challenging tasks. This shift in auditors' focus is consistent with previous research by Fedyk et al. (2022), Kend and Nguyen (2020) and Vitali and Giuliani (2024), which found that automating manual tasks shifts auditors' focus to important areas that require professional judgement or critical evaluation.

Another important finding regarding the auditor-AI relationship and changes in the auditor’s role is that the future role of auditors will likely include some form of AI supervision. Interviewees emphasised that the ultimate responsibility remains with the auditor because AI cannot be held responsible for anything. Consequently, they stated that AI-generated results must always be reviewed by a human auditor. This view is supported by Kokina and Davenport (2017), Moffitt et al. (2018) and Kokina et al. (2025) who expect auditors’ future role to shift to verifying AI-generated results, supervising machines, and developing AI tools. This finding also further supports the idea of human-AI coexistence as human auditors will likely work alongside AI systems.

In addition to the changes to auditors' existing roles, the findings suggest that AI can create new opportunities for auditing by expanding audit service offerings. A few interviewees believe that the use of AI might lead to more consultative services within auditing. This finding is supported by Mpofu (2023), Abu Huson et al. (2024) and Nguyen et al. (2024), who believe that the changes in auditing could open possibilities for consulting and advisory services. However, a few interviewees emphasised that auditors cannot offer direct advisory services. One interviewee also mentioned that AI could turn auditing into a continuous process instead of a yearly report. Previous research by Tiberius and Hirth (2019) and Leocádio et al. (2024) also expects that the implementation of AI can transform auditing from an annual audit to continuous, real-time auditing.

The changes in the auditor’s role can also affect auditors' skill requirements. This study's findings suggest that AI use in auditing requires auditors to improve and acquire certain competences and skills to succeed in an AI-driven environment. Similar findings have been made by Law and Shen (2024) and Moffitt et al. (2018) who found that as auditors' roles change with AI implementation, so do the necessary skills to succeed. The findings of this study suggest that the most essential competences for future auditors are technological skills, knowledge of core accounting principles, soft skills, social skills and analytical thinking. The interviewees agreed that to be able to use AI tools effectively, auditors should gain technological skills. Previous research by Sanoran and Ruangprapun

(2023), Vitali and Giuliani (2024), and Nguyen et al. (2024) supports this finding by reporting that data-analytic and technology skills will be essential for auditors to use AI effectively. The interviewees also believe that knowledge of core accounting principles will be increasingly important in evaluating and challenging AI outputs in the future. This finding has not been discussed in previous literature and can, therefore, be considered novel. This may be because AI use in auditing is still in the early stages, and therefore, prior studies have examined it from a more theoretical perspective, while this study aims to present the current real-world experiences. Another finding is that interviewees believed that the importance of social and collaboration skills will be emphasised in the future. Previous research by Law and Shen (2024) supports these findings, as they found that soft skills will be essential as auditors communicate with customers. However, this study suggests that social skills, especially, will be important among other soft skills. A few interviewees mentioned that analytical thinking will be important for auditors to use and adapt AI-generated results in the future. While previous studies have not confirmed this exact finding, very similar results have been obtained by Abu Huson et al. (2024), who found that critical thinking skills, professional scepticism, and professional judgement are essential for auditors to succeed in the future.

In summary, the findings suggest that AI will not replace auditors but instead augment auditors’ capabilities. According to the findings, human auditors will remain necessary in areas that require social interaction and professional judgement, which AI cannot replace. The results indicate that human auditors will work alongside AI systems in hybrid teams, which portrays coexistence in the auditing context. This study also found that the opinions on future auditor employment were divided, as half of the interviewees believed that the number of auditors could decrease, while the other half believed that the number of auditors would not decrease or might even increase. The findings also suggest that auditors' work will change with the use of AI in auditing in three ways. First, as AI can complete manual tasks, auditors' focus can shift towards more analytical and challenging tasks. Second, as AI becomes more widely used, auditors’ work will likely include supervising AI tools. Third, AI opens new opportunities in auditing to expand service offerings to consulting and continuous auditing. The findings also indicate that technical skills, knowledge of core accounting principles, soft skills, social skills, and analytical thinking are important for success in an AI-driven audit environment.

7.5 Updated theoretical framework

The original theoretical framework presents the relationships between relevant theories, concepts and findings regarding the three research questions (1) the potential changes in the role of auditors in international auditing firms from the perspective of AI automation and augmentation, (2) the benefits of AI automation and augmentation for international auditing firms and (3) the challenges of AI automation and augmentation for international auditing firms. It revolves around two main theories, which are the automation-augmentation paradox by Raisch and Krakowski (2021) and the coexistence of humans and AI by Einola and Khoreva (2023). Another central concept is the co-piloted audit model (Gu et al., 2024) which is a similar concept to coexistence, but in an auditing context.

The empirical findings support the view that AI will not replace auditors with automation but instead augment auditors' capabilities by assisting them. This confirms previous studies by Dhamija and Bag (2020), Hasan (2022), Mackenzie (2025), Nguyen et al. (2024), Tiberius and Hirth (2019) and Vitali and Giuliani (2024), who found that AI will not replace auditors but assist auditors in their work, augmenting their capabilities. The findings of this study also indicate that auditors and AI will coexist in organisations, as AI is being implemented into audit teams alongside human auditors. Further implications of human-AI coexistence in the auditing context are that many interviewees perceived AI as a team member, coworker or assistant. The integration of AI systems into auditing suggests that human auditors will be working alongside AI systems, supervising them and reviewing their output. These findings also align with the co-piloted auditing model proposed by Gu et al. (2024) in which auditors and AI systems collaborate, enhancing each other's strengths.

However, some novel findings emerged from the interview data (1) AI automation could improve auditors' work experience (2) the lack of data standardisation and resistance to change can hinder AI use (3) competences such as knowledge of core accounting principles, social skills, and analytical thinking will be increasingly important for auditors in the future AI-driven environment. The original theoretical framework has been updated to include these findings, better reflecting the current situation in practice (see Figure 8).

The empirical findings revealed an unexplored benefit of improved work experience. Two interviewees stated that AI automation improves auditors' work experience by allowing them to use their full potential on more challenging tasks. While this benefit was not discussed in previous research, a study by Cooper et al. (2022) found that accounting executives believed RPA would improve job satisfaction, while lower-level employees did not report effects on work satisfaction. While the study focuses on accounting instead of auditing and RPA instead of AI, the findings could be relevant to AI in an auditing context. However, due to the limited number of interviewees reporting this benefit and the lack of previous research, further research is needed to fully confirm the effects of AI automation on auditors' work experience.

The interview data also revealed the challenge of data standardisation. Four interviewees reported that the lack of standardisation in client systems can make AI use challenging and time-consuming, as the data must be manually edited. Therefore, interviewees stated that AI use in smaller clients is not profitable. While this finding was not widely discussed in previous literature, Kokina and Davenport (2017) found supporting evidence, noting the lack of data consistency across clients as one main barrier to AI implementation in auditing. With partial support from previous research, this study suggests that the lack of standardisation is a challenge for AI use in auditing.

The findings also highlighted the challenge of auditors' resistance to change. Five interviewees mentioned that auditors' resistance to adopting new tools is a challenge. While this challenge was not commonly mentioned in previous research, Abu Huson et al.

(2024) found that resistance to change is a challenge for implementing modern technologies in auditing. Considering the number of interviewees reporting this challenge and the support from previous research, the findings indicate that auditors' resistance to change can be considered a challenge for AI use.

The findings of this study also show that interviewees believe that knowledge of core accounting principles, social skills, and analytical thinking will be increasingly important in the future. Six interviewees reported that knowledge of core accounting principles will be important to evaluate and challenge AI’s results. This has not been discussed in previous research and can, therefore, be considered a novel finding. Six interviewees also brought up the importance of social skills for auditors in the future. While this has not been widely discussed in previous research, similar findings have been made by Law and Shen (2024) who found that soft skills will be important for auditors to communicate effectively with customers. Therefore, this study suggests that soft skills, especially social skills, will be essential in the future. Four interviewees also mentioned analytical thinking as an important competence for the future auditor. While previous studies have not confirmed this exact finding, very similar results have been obtained by Abu Huson et al. (2024) who found that critical thinking skills, professional scepticism, and professional judgement are essential for auditors to succeed in the future. Therefore, this study found evidence that auditors should have strong knowledge of core accounting principles, social skills and analytical thinking skills to succeed in the future.

In summary, the updated theoretical framework builds on the original framework developed from the relevant concepts and theories in the literature. The theoretical framework has been updated to include findings from the empirical data (see Figure 8). The findings suggest that (1) AI automation could improve auditors’ work experience, (2) the lack of data standardisation and resistance to change can hinder AI use, and (3) competences such as knowledge of core accounting principles, social skills, and analytical thinking will be increasingly important for auditors in the future AI-driven environment. The updated theoretical framework aims to provide a current and practical view of the situation.

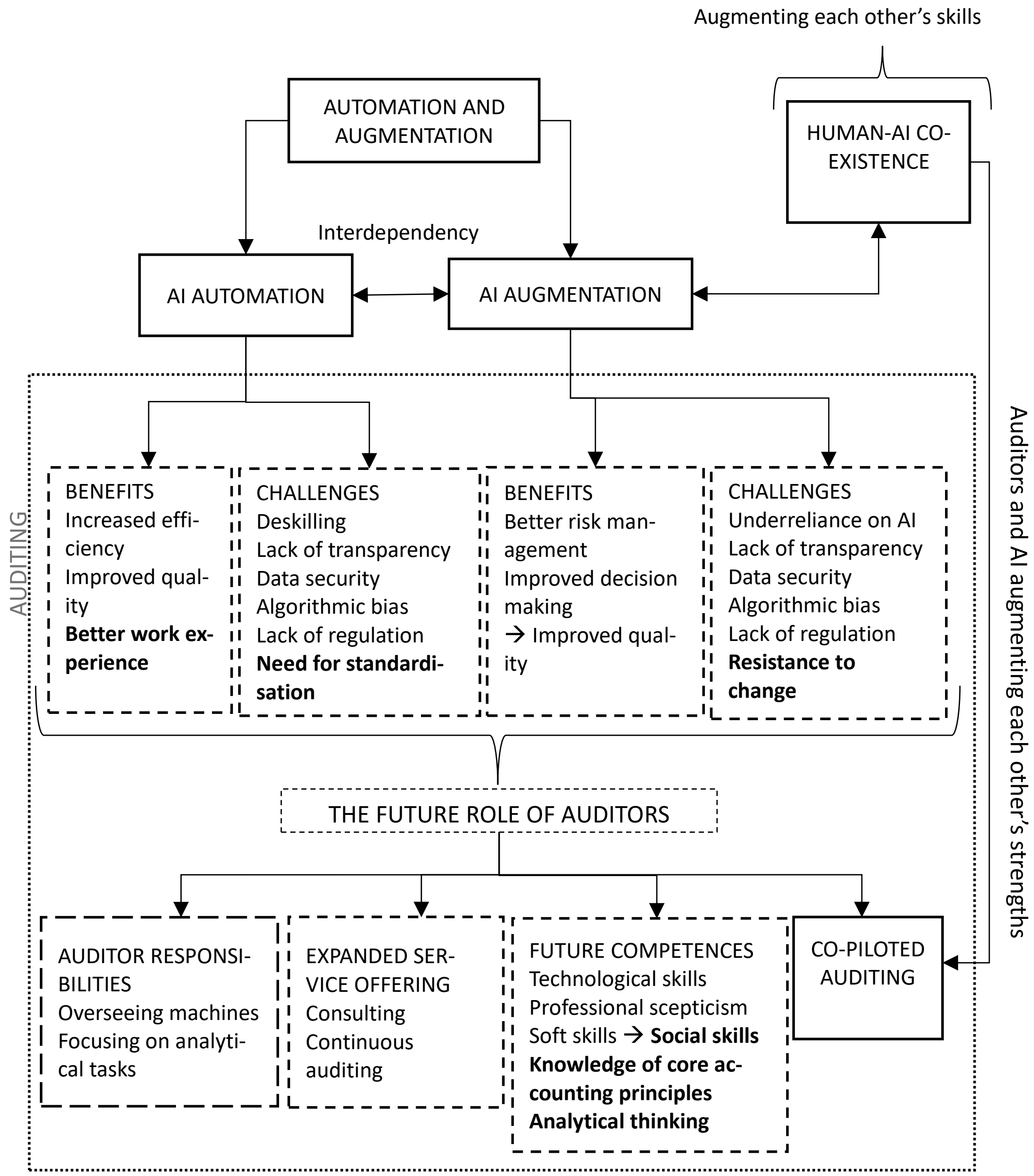

Figure 8. Updated theoretical framework.

8 Conclusions

This chapter presents the key findings, practical implications, limitations, and future research suggestions. First, the key findings are presented by answering the research questions. Then, practical implications for international auditing companies, auditors, and regulators are provided. Finally, the study’s limitations are explored, and future research suggestions are given.

8.1 Key findings

This chapter summarises the study’s key findings by answering the three research questions.

RQ1: How will AI automation and augmentation affect the auditor’s role in international audit companies?

The findings indicate that AI will not replace auditors but augment their capabilities. While the application of AI in auditing firms is still at an early stage, the findings suggest that AI will reshape the auditors' role in the future. As AI systems automate routine tasks, human auditors' focus will shift towards more challenging and analytical tasks. The findings suggest that the future of auditing will include the coexistence of human auditors and AI as the team structure changes to include AI systems and humans. The auditor's role will likely involve working alongside AI in a supervisory role. The responsibility will remain with the human auditor, as responsibility cannot be given to AI, so human auditors must review AI-generated information. Implementing AI into auditing could also expand the auditor’s role towards continuous auditing and advisory services. The findings also suggest that auditors should possess technological skills, analytical thinking, soft skills, social skills, professional scepticism, and knowledge of core accounting principles to succeed in this new AI-driven environment.

RQ2: How will international auditing companies benefit from AI automation and augmentation?

The findings suggest that international auditing firms can benefit from AI use through increased efficiency, enhanced quality, better risk detection and improved work experience. AI can automate manual and routine tasks, reducing audit time, human error and auditor workload, ultimately increasing efficiency and quality. The automation of routine tasks also shifts auditors' focus to more challenging areas, allowing auditors to use their full capacity and brain power, which can lead to improved work experience. AI can also assist auditors in risk detection by detecting anomalies and flagging high-risk areas for further inspection, augmenting human capabilities and improving risk detection.

RQ3: How do AI automation and augmentation challenges affect international auditing companies?

The results of this study indicate that international auditing firms can also face significant challenges in AI implementation and use. The most common challenges are a lack of trust, transparency, regulation, data standardisation, and overreliance on AI. Data security and confidentiality were also mentioned, but they were not seen as direct challenges but as high-risk factors to consider. Auditors hesitate to trust AI outputs because of AI's non-transparent nature, which could result in underreliance on AI. The findings imply that the effective use of AI would require AI to have a transparent and explainable output. Another major challenge is that AI requires standardised data, which means that client data must often be manually edited, which uses resources and is not cost-effective. Overreliance on AI could have a negative effect on audit quality. If auditors rely too much on AI, it could also reduce learning opportunities for auditors, potentially leading to the deskilling of auditors. The main barrier to AI use in auditing firms is the lack of regulation on AI use in auditing, which results in companies being unsure of how AI can be applied.

8.2 Theoretical contributions

This study makes several theoretical contributions. First, it addresses the literature gap on the effects of automation and augmentation on the auditor’s role by extending the automation-augmentation research into the auditing context. This study supports previous research (Dhamija & Bag, 2020; Hasan, 2022; Mackenzie, 2025; Nguyen et al., 2024; Tiberius & Hirth, 2019; Vitali & Giuliani, 2024) on the view that AI is not expected to automate auditing, but rather its role is considered more augmentative. However, this study supports the paradoxical view of automation and augmentation by Raisch and Krakowski (2021), as the findings indicate that both automation and augmentation are present at the same time, which aligns with the view of Einola and Khoreva (2023). For example, AI can automate routine tasks, which shifts the auditor's focus to more challenging tasks, simultaneously augmenting the auditor’s competences.

Second, this study expands the concept of human-AI coexistence by Einola and Khoreva (2023) into auditing. The findings indicate that human auditors and AI will coexist in organisations as AI is implemented into teams alongside human auditors. The findings also show that many interviewees perceived AI as a team member, coworker or assistant, implying that auditors and AI will collaborate closely. This supports the idea by Einola and Khoreva (2023) that organisations should consider AI a coworker instead of a tool for successful coexistence. Interviewees expressed further implications of auditor-AI coexistence, as human auditors will likely supervise AI systems and review their output.

Third, based on the findings of coexistence in the auditing context, this study provides empirical evidence to support the co-piloted model presented by Gu et al. (2024), which suggests that human auditors and AI systems could collaborate, enhancing each other’s strengths. While their study focused on the technical implementation of this concept, this study provides insight into its real-world application. The findings suggest that auditors and AI will coexist in organisations, aligning with the proposed co-piloted auditing model.

Fourth, this study adds to the existing research on AI's benefits, challenges and future competences. This study identified novel findings that AI’s need for standardised data and auditors' resistance to change are considered challenges for AI use. The study also found preliminary evidence that AI automation can improve auditors’ work experience by allowing them to focus on more challenging tasks and use more of their brain capacity. This study also expands previous research on the most important future competences for auditors by identifying additional competences. The findings of this study indicate that core accounting knowledge, analytical thinking and social skills will also be essential for auditors in the future.

8.3 Practical implications and recommendations

Due to its focus on the real-life effects of AI on the auditor’s role, this study presents multiple practical implications and recommendations. First, the findings suggest that the increased use of AI will not remove the need for human auditors, as they will remain essential in the foreseeable future. Even though opinions were divided on whether AI would reduce the number of auditors, the consensus was that AI would not completely replace auditors but instead assist them. Implementing AI is expected to change the auditor’s role and create new opportunities for audit firms. Therefore, audit firms are recommended to focus on expanding their services and supporting auditors during the transformation instead of reducing the number of auditors.

Second, the results indicate that human auditors and AI will work together in hybrid teams consisting of human auditors and AI systems. This means audit firms should encourage human-AI coexistence in the organisation and help auditors adapt to the new team structure.

Third, the findings suggest that AI will change auditors’ responsibilities in two ways. First, automating routine tasks will shift auditors' focus to more complex and analytical tasks that AI cannot do. Second, auditors' work will likely involve supervising AI systems and reviewing their output. The changes in auditors' roles affect the competences that auditors should possess in the future. The most important identified competences were strong knowledge of accounting principles, technological proficiency, analytical thinking, soft skills, social skills and professional scepticism. Therefore, auditors are advised to develop these skills and competences actively to succeed in the future audit environment. Audit firms are recommended to provide additional training for technology use and accounting principles to ensure auditors can effectively use AI and challenge its output.

Fourth, the findings indicate that the use of AI can benefit auditing companies. The results suggest that automating routine tasks can increase efficiency and quality by reducing time and human error. Automation also allows auditors to focus on more complex tasks, which may improve their work experience. Audit firms should consider implementing AI automation for manual tasks to take full advantage of these benefits.

Fifth, this study also found multiple challenges to AI use and implementation, including a lack of transparency, regulatory uncertainty, the need for standardised data, and resistance to change. To mitigate these challenges, audit firms are recommended to develop transparent AI systems to enhance transparency, establish internal principles for responsible AI use, standardise their internal audit processes to simplify AI implementation, and implement effective change management strategies to support the transition and reduce resistance from auditors. Firms can also provide more knowledge on the benefits of AI to mitigate the auditors' potential resistance to change. Regulators and standard-setting boards are recommended to provide clear instructions on appropriate AI use in auditing and to create more specific rules for accounting to increase its standardisation.

8.4 Limitations and future research suggestions

Although this study provides valuable insight into the impact of AI automation and augmentation on the role of auditors in international auditing firms, its limitations should be acknowledged. This study is qualitative and therefore consists of a relatively small sample size of 9 interviewees, which might affect the generalisability of the findings. Also, while this study specifically focused on international audit firms operating in Finland, it is important to note that this geographic scope may affect the global applicability of the findings. Finally, since AI adoption in auditing is still in its early stages and this study focuses on the anticipated changes to the auditors' role, the findings reflect future expectations and perceptions.

Based on this study's implications and limitations, there are multiple suggestions for future research. First, as this study is qualitative, it would be beneficial to conduct a quantitative study on the effects of AI automation and augmentation on the auditors' role to confirm the findings of this study and create more generalisable results. A globally executed survey would provide insight internationally, allowing for comparison between countries.

Second, future research could explore how the changes in the auditor's role affect auditing education. This study found many important future competences for auditors, so it would be valuable to evaluate whether these are currently applied in auditing education. A multi-method study that compares current curricula to the identified essential future competences could discover potential gaps between current education and expected competences. This study could offer practical guidance to educational institutions on updating the curriculum to best respond to the future competences expected from auditors.

Third, this study found preliminary evidence that automating routine tasks could improve auditors' work experience. These findings could be confirmed with a mixed-method longitudinal study that examines how AI use influences job satisfaction and employee retention in auditing firms. This could be done through a large-scale job satisfaction survey and employee turnover analysis. In addition, employee interviews could be conducted to gain a deeper understanding of their experiences.

Finally, as this study's findings on auditors' employment were divided, future research could further explore the effects of AI on the number of auditors. A longitudinal quantitative study could provide insight into how AI affects the number of auditors in different organisational levels and roles over a more extended period.

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Appendices

Appendix 1. Interview questions

Section 1: Background and Professional Experience

1. Can you briefly describe your job role, responsibilities and experience?

Section 2: The Use of Artificial Intelligence in Auditing

2. Does your company use generative AI or other AI technologies, such as machine learning, natural language processing, computer vision, or expert systems, to support auditing?
    - How long have you been utilizing various AI technologies in auditing?
    - How are they used?
3. What kinds of AI tools are you developing? (only for technology-focused interviewees)
    - What is the expected timeline for the implementation of new AI tools?
    - What are the biggest obstacles to their adoption?
4. What tasks has AI automated/could automate in the future?
5. How does AI support/could support auditors in their work?
    - Are there tasks where AI initially assisted auditors but later could perform independently?
    - Are there tasks where AI cannot be used at all? Why?

Section 3: Benefits and Challenges of AI in Auditing

6. Has AI brought benefits to auditing?
    - If yes, how are these benefits visible in practice?
7. What opportunities could AI bring to auditing in the future?
8. Are there challenges regarding the use and adoption of AI?
    - If yes, how are these challenges visible in practice?
9. What challenges could AI use in auditing create in the future?

Section 5: The Future of Auditing with AI

10. Could you share your opinion on the following statements? Do you agree or disagree? Why?
    - AI will replace auditors in the future.

- AI supports auditors in their work.
- The number of auditors will decrease in the future due to AI.
- AI will create new job roles in the auditing industry.
    - If yes, what kind of jobs?

11. How do you believe AI will affect the role of auditors in the future?
12. Will AI change the skill requirements or qualifications for auditors?
    - If yes, how?
13. What auditor skills do you consider the most important in the future?
14. How do you see the future relationship between auditors and AI?

Closing Questions:

15. Would you like to add anything regarding the impact of AI on auditing?
16. Do you have any questions?