The Influence of Generative AI on Auditors' comfort

How does generative AI influence auditors' comfort in verifying and assessing AI-generated financial data?

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Abstract

Background: Generative Artificial intelligence **(**AI) is becoming increasingly prominent across society, including the auditing profession. Generative AI enhances audit quality by improving fraud detection and enabling the processing of larger data volumes. However, these advantages also challenge auditors' roles, skillsets, and professional judgment. These changes raise questions about how auditors experience comfort and trust when working with data produced by generative AI.

Purpose: This study aims to explore how the implementation of generative AI affects auditors, with a particular focus on their comfort and psychoemotional responses to changes in their work.

Method: This study adopts an abductive research approach and applies a qualitative methodology. Data was collected through ten interviews with auditors and analysed through a thematic analysis.

Conclusion: The study shows that generative AI's integration into auditing is not merely a technical shift but a reconfiguration of how auditors build comfort, exercise judgment, and develop trust in their tools. Comfort is influenced by transparency, institutional support, and the extent to which human oversight remains central. While discomfort persists—particularly in complex or judgment-heavy tasks—the findings suggest that with proper training, clear implementation, and strategic alignment, generative AI can enhance both professional development and audit quality.

Contribution: This study contributes to Comfort Theory by proposing an alternative model of comfort more aligned with the realities of auditing and other technology-intensive profession.

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List of Abbreviations

ADA	Audit Data Analytics
AI	Artificial Intelligence
GDPR	General Data Protection Regulation
IAASB	International Auditing and Assurance Standards Board
IFRS	International Financial Reporting Standards
ML	Machine Learning
NLP	Natural Language Processing
PCAOB	Public Company Accounting Oversight Board

Declaration

We hereby declare that this thesis represents our own work.

We declare that we have obtained the necessary ethical approval (e.g., GDPR) and acknowledged our obligations and the rights of the participants in the research.

We have read and applied the Jönköping University's current research ethics guidelines with regards to the use of artificial intelligence (AI) tools in this work as presented in the Course Guide. During the preparation of this work the authors used the following AI tools and the purpose for their use.

- Primo search – For literature searches
- Google Scholar – For literature searches
- ChatGPT – For text structure & grammar
- Cockatoo – For transcribing
- Microsoft Teams – For transcribing

As authors, we have reviewed and edited the content as needed and take full responsibility for the content of the thesis.

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1 Introduction

The first chapter introduces the background and context of the study. It outlines the research problem, presents the purpose of this study, and discusses its overall significance.

1.1 Background

Financial auditing is a profession focused on examining financial records to ensure that companies are fairly represented and in accordance with applicable laws and regulations (Kueppers & Sullivan, 2010). The profession arose to help stakeholders, such as investors, creditors, and the government, ensure that the financial reports are relevant and provide useful information to them (Ghandar, 2022). Auditors review operations and inventories to access compliance with standards such as IFRS and national laws (Haraldsson & Tagesson, 2014). Therefore, auditing is crucial for the legitimacy of companies (Van Brank et al., 2022). By acting as an independent party, auditors also help foster trust between companies and their shareholders by verifying the fairness of financial reporting (Kueppers & Sullivan, 2010). Ultimately, auditing serves as a key mechanism for companies to signal their sustainability and credibility to external audiences, thereby attracting investors and enhancing their reputation (Ghandar, 2022).

Traditionally, auditing has relied heavily on manual processes (Tehrani & Ghorbani, 2013). Auditors manually collect information, including receipts and supporting documents, to verify financial transactions. However, as auditors cannot review all documentation, they apply sampling methods to obtain a representative overview of the financial records (Ponemon & Wendell, 1995). In addition, auditors manually cross-check balance sheets and other financial statements, comparing data both within the same period and across different years to ensure consistency and accuracy (Pentland, 1993). The profession is therefore grounded on time-consuming tasks that require auditors to possess a strong understanding of both sampling techniques and accounting principles (Ponemon & Wendell, 1995). The audit process is further supported by standardized procedures derived from professional frameworks, which guide auditors in applying their professional judgment effectively (Pentland, 1993). These established

routines help ensure that auditors' expertise is consistently and appropriately applied throughout the audit.

Since the 1950s, with the development of Artificial Intelligence (AI) (Sandewall, 2014), machines have gradually gained the ability to learn and mimic human behaviour (Haenlein & Kaplan, 2019). The rise of machine learning has enabled AI to recognize and learn patterns, effectively replicating human behaviour (Shao et al., 2022). Early advancements in AI allowed computers to automate many of the routine, time-consuming tasks that auditors encounter daily (Chen & Williams, 2022). More recently, the emergence of generative AI has marked a significant advancement, moving beyond pattern recognition to the creation of original content—including text, images, and even financial reports (Feuerriegel et al., 2024). This evolution is rapidly transforming various professions, including auditing, by automating both administrative and analytical functions (Fedyk et al., 2022).

Unlike traditional AI, which focuses on rule-based automation, generative AI can generate financial summaries, risk assessments, and anomaly reports by synthesizing vast amounts of financial data (Anica-Popa et al., 2024). This capability is transforming the auditing process. Generative AI can analyze entire datasets instead of relying on sampling, reducing the risk of missing critical discrepancies (Kokina & Davenport, 2017). It also enables real-time fraud detection, adapting dynamically to evolving financial irregularities (Issa et al., 2016). Furthermore, generative AI can interpret financial narratives, identifying inconsistencies between financial reports and disclosures, which traditionally required human judgment (Haenlein & Kaplan, 2019).

Although AI is reshaping the auditing profession, it does not eliminate the need for human expertise (Brougham & Haar, 2018). Instead, it redefines the role of auditors, who are increasingly dependent on AI-generated outputs, even though these processes are not always transparent (Brougham & Haar, 2018). As AI becomes further integrated into auditing, auditors must adapt by developing a deeper understanding of AI systems, their capabilities, and limitations (Ivakhnenkov, 2023). The profession is moving toward a more interpretative role, where auditors assess AI-generated findings rather than directly engaging with raw financial data (Almufadda & Almezeini, 2022). This shift raises questions about how auditors maintain confidence in their work and how comfortable they feel relying on AI-driven processes.

Institutional forces play a significant role in shaping the evolving responsibilities of auditors, as external pressures push for the adoption of AI despite potential discomfort among professionals (Handoko et al., 2024). The rapid integration of AI has reshaped norms, regulations, and industry expectations, requiring auditors to develop new competencies beyond their traditional expertise (Law & Shen, 2024). However, the lack of transparency in AI systems makes it challenging for auditors to fully trust or verify their outputs, reinforcing a sense of unease as they navigate these changes (Bathaee, 2018). With limited time to adapt, auditors may find that their conventional skillsets are not always directly applicable, raising concerns about their level of control over audit processes in an increasingly AI-driven environment (Almufadda & Almezeini, 2022).

This shift in skillset and responsibility has profound implications for auditors' sense of comfort, Comfort, in this context, refers to the confidence and assurance auditors derive from their expertise, tools, and routines (Carrington & Catasús, 2007). As auditors' roles evolve, comfort relies on well-established systems designed to ensure the trustworthiness of their processes (Law & Shen, 2024). With AI being integrated into audits, auditors are increasingly tasked with interpreting AI outputs rather than engaging with original verifications (Almufadda & Almezeini, 2022). This shift can create uncertainty, particularly regarding the functionality, limitations, and reliability of AI algorithms (Hedman et al., 2015).

The integration of AI into auditing introduces both benefits and challenges (Abdullah & Almaqtari, 2024). Key benefits include enhanced efficiency and accuracy in audits, as AI can detect anomalies more quickly than human auditors (Issa et al., 2016). AI also improves audit quality by identifying fraud patterns more easily, thus strengthening fraud detection (Fedyk et al., 2022). The ability to analyse large datasets in-depth improves the overall trustworthiness of audits, which is essential for maintaining the credibility of financial reporting (Law & Shen, 2024). Moreover, AI-driven tools allow for a more thorough review of financial data, reducing the likelihood of errors and oversight (Omoteso, 2012). By automating routine tasks such as data entry and reconciliations, AI enables auditors to focus on more complex analytical tasks, ultimately enhancing the quality and depth of their evaluations (Almufadda & Almezeini, 2022).

Despite these advancements, it is critical that auditors receive adequate training and integration of AI systems to fully realize the potential benefits of AI (Jeong & Kim, 2019). Without proper implementation, the effectiveness of AI could be compromised, negatively impacting audit quality (Brougham & Haar, 2018). While AI improves audit quality and efficiency, auditors must also develop new skills to adapt to these changes (Ivakhnenkov, 2023). Although traditional auditing expertise remains relevant, auditors now need to focus on client communication and overseeing AI systems, rather than manually conducting all tasks (Almufadda & Almezeini, 2022). This transition may reduce auditors' control over the audit process, which could, in turn, affect their confidence in their work, despite higher audit quality (Lombardi et al., 2021).

As AI continues to integrate into auditing, auditors' perceptions of their job security play a key role in their trust toward the technology (Xiong, 2024). Concerns about being replaced by AI can lead to scepticism, affecting how auditors interact with AI-generated outputs and, ultimately, the effectiveness of AI integration (Gerlich, 2023). Yang (2024) also argue that AI adoption affects employees' psychological contracts, impacting both job engagement and trust in the technology. When AI is seen as a potential job threat, auditors may feel insecure, leading to a decline in their trust in the system (Yang, 2024). However, when AI is viewed as a tool that enhances their work rather than replacing it, auditors are more likely to trust it (Rahwan et al., 2019). This sense of security is further reinforced when auditors receive training to work alongside AI, which boosts their confidence and comfort with the technology (Malik et al., 2022). In this way, auditors' trust in AI is influenced by both their comfort with the technology and their sense of job security in an evolving landscape.

1.2 Problematization

The adoption of generative artificial intelligence (AI) in auditing has reshaped auditors' roles, shifting key tasks such as data analysis, anomaly detection, and fraud identification from human professionals to AI systems (Issa et al., 2016). Historically, auditing relied on manual checks, professional scepticism, and established procedures to ensure accuracy and reliability (Pentland, 1993). Today, generative AI can process vast amounts of data and identify irregularities at a scale beyond human capability, increasing efficiency and potentially improving audit quality (Omoteso, 2012). However, while generative AI is assumed to assist auditors in performing higher-quality audits (Novizhilova et al., 2024), its integration raises

new concerns about auditors' ability to verify and assess AI-generated financial data. Unlike traditional auditing methods, where auditors directly engage with financial records, generative AI introduces a layer of uncertainty, making it difficult to fully understand how conclusions are reached (Lipton, 2018). This challenges auditors' ability to exercise professional judgment and ensure the reliability of audit findings, which has consequences on their sense of comfort.

Comfort Theory assumes that individuals seek to reduce uncertainty by relying on familiar and transparent systems that allow them to exercise control over their work (Carrington & Catasús, 2007). Traditionally, auditors have gained comfort in their role through established processes that ensure audit quality and accountability. The introduction of generative AI challenges these notions, as auditors are now expected to interpret and rely on AI-generated outputs without fully understanding how they were produced (Almufadda & Almezeini, 2022). If auditors cannot fully verify AI-generated financial data, their ability to trust audit conclusions may be compromised, leading to discomfort and potential resistance to generative AI adoption.

Simultaneously, institutional pressures accelerate generative AI implementation. According to Institutional Theory, organizations do not adopt technologies solely for technical benefit, but in response to regulatory mandates, competitive pressures, and professional norms (DiMaggio & Powell, 1983). These coercive and mimetic pressures may compel auditors to work with generative AI before they feel adequately prepared (Jeong & Kim, 2019; Law & Shen, 2024). As a result, generative AI adoption becomes not only a technological challenge, but a reflection of broader institutional forces that shape how auditors perceive and engage with innovation.

This pressure intersects with the personal dimension of trust. Trust Theory suggests that users are more likely to accept technology when they believe it is competent, reliable, and acts with integrity (Gefen et al., 2003). In auditing, trust depends not only on technical functionality, but also on system's ability to provide explanations and align with professional standards. However, AI's black-box nature—where decision processes are opaque—can hinder trust, especially when professional scepticism and contextual reasoning are essential (Bathaee, 2018; Sutton et al., 2016). Without transparency, auditors may struggle to engage critically with generative AI outputs, leading to hesitation in applying them to assurance work (Brynjolfsson & McAfee, 2017; Kokina & Davenport, 2017).

Beyond technical opacity, concerns about job displacement also affect auditors' trust in AI. Studies show that when technology is seen as a threat to employment, trust in its value diminishes (Bhargava et al., 2021; Brougham & Haar, 2018). If generative AI is viewed as undermining human roles rather than enhancing them, it can disrupt the psychological contract between professionals and their organizations (Braganza et al., 2021), eroding motivation, confidence, and trust in AI-generated conclusions.

Despite these concerns, several scholars suggest that discomfort may be reduced over time with proper training and experience (Abdullah & Almaqtari, 2024). Comfort Theory posits that familiarity and support structures can diminish initial resistance and enhance satisfaction in the long term (Kolcaba, 2001). While repeated AI use may help auditors develop new verification strategies (Venkatesh & Davis, 2000), this process is less straightforward when dealing with generative AI, which presents unique challenges due to its lack of transparency.

Adding to this complexity, current academic discourse tends to emphasize generative AI's benefits in enhancing efficiency and accuracy (Fedyk et al., 2022), but often overlooks the nuanced ways in which trust, control, and professional confidence are affected in practice. Brougham and Haar (2018), for example, highlight how automation contributes to job insecurity but do not examine its effects on auditors' willingness to rely on conclusions produced by generative AI. Similarly, scholars like Frey and Osborne (2017) and Huang and Rust (2018) focus on task replacement without addressing how this shift may undermine auditors' ability to critically evaluate complex audit outcomes. While Almufadda and Almezeini (2022) note that AI integration can disrupt auditors' sense of control, they stop short of linking this to broader trust dynamics.

In this rapidly evolving landscape, the integration of generative AI into auditing raises not only technical and procedural questions but also deeper concerns about how such systems shape professional identity and practice. As auditors continue to adapt to increasingly digital environments, it becomes essential to investigate how generative AI affects their trust, comfort, and ability to maintain professional scepticism (Morandini et al., 2023). Without such insight, firms risk prioritizing technological adoption at the expense of audit quality and institutional integrity (Bankins et al., 2024; Park et al., 2024). These gaps point to a need for deeper investigation into how auditors interpret and assess generative AI outputs when traditional

judgement-based cues are diminished. As Appelbaum et al. (2017) argue, the verification of financial information lies at the heart of the auditing profession, making this an urgent area for research.

1.3 Purpose

By examining auditors' perspectives and attitudes, this research aims to explore the challenges and dynamics of generative AI integration in the auditing profession. The rapid adoption of generative AI presents both challenges and opportunities, influencing auditors' comfort with their work quality, job security, and trust in AI-generated financial data (Brougham & Haar, 2018; Frey & Osborne, 2017; Issa et al., 2016). While generative AI has the potential to enhance audit quality and efficiency, its implementation may also introduce discomfort, as auditors adjust to shifting professional roles and must place trust in generative AI systems to uphold auditing standards (Almufadda & Almezeini, 2022; Fedyk et al., 2022). Existing frameworks explain why generative AI is adopted (Appelbaum et al., 2017; Omoteso, 2012), but they do not account for how auditors experience these changes, making it essential to explore generative AI's effects through the lens of comfort, trust, and institutional pressures.

This study applies Comfort Theory to examine how generative AI adoption influences auditors' sense of control and confidence in their work, Trust Theory to assess how lack of transparency affects their reliance on AI-generated data, and Institutional Theory to explore the external pressures shaping AI implementation (Jeong & Kim, 2019; Venkatesh & Bala, 2008). By integrating these perspectives, this thesis contributes to a deeper understanding of how generative AI affects auditors' ability to verify and assess financial data. Accordingly, this study seeks to answer the following research question:

- *How does generative AI influence auditors' comfort in verifying and assessing AI-generated financial data?*

2 Literature review

The second chapter will cover the literature review. The section begins with a methodology for the literature review, where the process of gathering data is presented. This is followed by a thorough discussion of the theoretical framework used to analyse the auditors' responses. Lastly, additional literature is presented to help provide a deeper understanding of the topic.

2.1 Literature review method

Throughout this literature review, various steps and methodologies were undertaken to find relevant sources. Our research question guided us in assessing the relevance of the articles we found, ensuring that everything contributed to answering it. The following outlines the methodologies used to identify, locate, and synthesize relevant literature for this study, ensuring a comprehensive evaluation of the available information and studies on the topic.

To find articles, we first referred to literature used in previous research on similar topics. As we were already familiar with these works, we deemed them appropriate to include. From there, we also examined studies referenced in these articles to determine if any were relevant. Building upon those sources, we conducted further searches using SCOPUS and Primo. To ensure we found relevant sources, we used key words such as "Generative AI in auditing", "Comfort + Auditing", "Trust Theory + Auditing", "Pro scepticism + Generative AI", "Audit quality", "Audit Data Analytics", "Job security + Generative AI" and "Institutional Theory". These searches generated thousands of articles, which we narrowed down by reading abstracts to assess their relevance to the study, followed by in-depth reading of the selected articles. Additionally, we looked at some bibliometric literature reviews on the different topics to gain insight into which articles were the main ones in the different topics, and to gather more literature to look through. We also used Primo Research Assistant to find specific critiques of various theories, ensuring we incorporated sufficient nuance in our selected literature.

The primary criteria for including or excluding articles, aside from relevance, was whether the articles were published in a peer-reviewed journal. We decided to include mostly peer-reviewed articles to enhance the credibility of our sources (Aggarwal et al., 2022). However, as AI,

especially generative AI, is a rather new topic of studies, we decided to include some articles that are published in less credible journals, since those articles were the only studies done on the specific topics we were discussing. We also chose to only include articles written in English, as it is the primary language for similar research. Some books were also included, as they provided a broader perspective that helped us better understand the topics.

2.2 Theoretical framework

2.2.1 Institutional Theory

Institutional Theory, initially developed by early sociologists such as Philip Selznick (1949) and later expanded by John Meyer and Brian Rowan (1977) as well as Paul DiMaggio and Walter Powell (1983), seeks to explain how institutions shape organizational structures, behaviours, and decision-making processes. The theory posits that organizations do not operate solely based on rational efficiency but are influenced by social norms, cultural expectations, and institutional pressures (DiMaggio & Powell, 1983; Meyer & Rowan, 1977; Selznick, 1949). Institutions provide the formal and informal rules that organizations follow to gain legitimacy, which in turn affects their survival and success. Over time, the theory has evolved into two distinct streams: old institutionalism and new institutionalism. Powell and DiMaggio (1991) suggest that the old and new institutionalisms identify different sources of constraint, with the older focusing on internal organizational dynamics, such as political trade-offs and alliances, while the new emphasizes legitimacy, stability, and the power of common understandings that shape organizational behaviour (Powell & DiMaggio, 1991). Institutional Theory is widely applied in organizational studies to understand why organizations within a particular field exhibit similarities despite differences in their internal structures and strategies.

A central assumption of Institutional Theory is that organizations conform to external expectations to secure legitimacy, resources, and stability (DiMaggio & Powell, 1983). Meyer and Rowan (1977) and DiMaggio and Powell (1983) introduced the concept of institutional isomorphism, which suggests that organizations tend to adopt similar structures and practices over time due to coercive, mimetic, and normative pressures. Coercive isomorphism arises from external forces such as regulatory requirements or government mandates that compel organizations to adopt certain practices (Mizruchi & Fein, 1999). Mimetic isomorphism occurs when organizations imitate others, particularly in situations of uncertainty, to enhance their legitimacy (Mizruchi & Fein, 1999). Normative isomorphism is driven by professionalization,

where shared norms, educational standards, and industry expectations shape organizational behavior (Mizruchi & Fein, 1999). These mechanisms explain why organizations within an institutional field often resemble each other, even when their operational needs differ.

Institutional logics are another key concept within Institutional Theory, referring to the broader belief systems that shape organizational behaviour and decision-making. Thornton and Ocasio (1999) argue that institutions operate within multiple logics, such as market logic, bureaucratic logic, or professional logic, which influence how organizations prioritize different goals and strategies. Organizations must navigate these competing logics to maintain both legitimacy and operational effectiveness. In the auditing profession, institutional logics play a crucial role in shaping how firms operate (Guénin-Paracini et al., 2015). The profession is largely influenced by professional logic, which emphasizes compliance with ethical standards, regulatory requirements, and scepticism in financial reporting. At the same time, market logic pushes firms toward commercial considerations, such as profitability, client retention, and service expansion (Anderson-Gough et al., 2000). The coexistence of these logics can lead to tensions, as firms must balance their responsibility to uphold audit quality with the pressures of maintaining competitiveness in the market (Thornton and Ocasio, 1999).

While Institutional Theory offers valuable insights into how external pressures shape organizational behaviour, it is important to also acknowledge the role of human agency in navigating these pressures (Battilana et al., 2009). Leaders and key decision-makers within organizations exercise agency by interpreting institutional logics, adapting strategies, and sometimes challenging or resisting conformity to external expectations (Seo & Creed, 2002). This explains why organizations, even within the same institutional field, may respond differently to similar regulatory pressures or market demands (Oliver, 1991). The variation in organizational responses reflects the active role of individuals and groups within organizations in making decisions that balance both institutional expectations and their own strategic objectives (Powell & Colyvas, 2008). In auditing, for instance, while firms face coercive pressures from regulations and normative pressures from professional standards (DiMaggio & Powell, 1983; Meyer & Rowan, 1977), human agency enables firms to adapt and shape their responses based on their unique cultures, priorities, and leadership decisions (Guénin-Paracini et al., 2015; Thornton & Ocasio, 1999).

However, while Institutional Theory is instrumental in explaining how external forces shape auditing practices, it does not fully address the evolving challenges posed by the integration of emerging technologies like generative artificial intelligence (Battilana et al., 2009). The theory's emphasis on stability and legitimacy-seeking behaviour can sometimes obscure the dynamic nature of technological adoption within the profession (DiMaggio & Powell, 1983). While audit firms face coercive isomorphism through regulatory frameworks and industry standards (Haapamäki, 2022), they also encounter resistance to generative AI adoption due to institutional constraints, such as risk aversion, cultural inertia, and reluctance to disrupt established professional norms (Freitas & Guimarães, 2007). These constraints have been cited as reasons for hesitation, particularly when generative AI is perceived to threaten audit quality, professional scepticism, or control over judgment processes (Guénin-Paracini et al., 2015; Power, 2003).

At the same time, some literature suggests that the relationship between institutional pressure and generative AI adoption is not solely defined by resistance. Adoption may proceed despite internal uncertainty—driven by mimetic pressures, market competition, or the desire to appear technologically progressive (Emett et al., 2023). In such cases, adoption may function more as a symbolic act of legitimacy than as a deeply embedded transformation. As Meyer and Rowan (1977) argue, organizations often implement new practices ceremonially to conform to external expectations, even if those practices are not fully integrated into daily operation.

This perspective broadens Institutional Theory's explanatory power, moving beyond resistance to include strategically motivated or ceremonial compliance. It also highlights how organizations may adopt generative AI without full internal alignment—raising important questions about the quality and sustainability of such integration. Firms with a growth mindset (Cao et al., 2022) or a long-term strategic orientation (Emett et al., 2023) may be more likely to implement AI meaningfully, balancing legitimacy with innovation.

2.2.2 Trust Theory

Trust is a key concept that highlights the willingness to be vulnerable to another party, based on the expectation that they will act in a predictable and beneficial manner (Shoorman et al., 2007). It is a dynamic relationship that evolves over time, influenced by new experiences and situations (Shapiro et al., 1992). Trust plays a crucial role in organizations, particularly in

leadership and team dynamics (Dirks & Ferrin, 2002). The theory examines how trust is formed, how it impacts decision-making, and how it is maintained (Cofta, 2021). Mayer et al. (1995) further identify three key factors that shape trust: ability, benevolence, and integrity, which together create the foundation for trust in any relationship.

The three components of trust can be described as follows: *ability* refers to the perceived competence of the party to be trusted (Mayer et al. 1995). It relates to the skills and knowledge of the party and is heavily reliant on context—a party may be trusted in one area where it has expertise but not in another where it lacks that expertise (Gefen et al., 2003). *Benevolence* refers to the perceived good intentions of the party (Shoorman et al., 2007). It indicates whether the party is seen as acting in the best interest of the other party rather than out of self-interest (Ehlers, 2021). Lastly, *integrity* refers to the perception that the party adheres to regulations and ethical principles (Nelson 2009). It means that the party acts consistently, reliably, and in alignment with shared values between the two parties (Shoorman et al., 2007). Therefore, a party is considered trustworthy when it demonstrates all three attributes— acting in the trustor's best interest while maintaining competence and ethical standards (Morgan & Hunt, 1994). The assessment of these attributes then influences the willingness of the trustor to take risks in relation to the trustee (Mayer et al., 1995).

Trust Theory has been applied in various fields, particularly in organizational leadership, where it explains the role of trust in team and leadership dynamics (Mayer et al., 2007). Dirks and Ferrin (2002) found that trust improves employee performance and job satisfaction, while Morgan and Hunt (1994) demonstrated that trust is essential for client retention, as it enhances customer satisfaction. The most relevant application of Trust Theory is within auditing where it helps explain the relationship between the auditor and client, as well as the trust placed in the accuracy of the audit and the honesty of the client (Hurtt et al., 2013). However, trust in auditing is not absolute; it must be balanced with professional scepticism. Nelson (2009) highlighted that while trust is necessary for effective auditor-client interactions, excessive trust can lead to the oversight of misstatements, making scepticism a critical counterbalance. Beyond the auditor-client relationship, trust in auditing also extends to shareholders, who must believe that auditors are capable of producing high-quality audits (DeFond & Zhang, 2014). Furthermore, Francis (2011) emphasized that adherence to regulations and standards are crucial for maintaining trust in auditors.

Trust Theory has also been applied to the use of technology and AI, particularly in understating how technology is used and accepted (Dennis, 2024). In this context, Trust Theory is used to assess how trustworthy technology is perceived to be (Siau & Wang, 2018). Siau and Wang (2018) found that the competence and benevolence of technology has a big effect on the level of trust placed in it. They also indicated that trust is influenced by the transparency of AI system, as when AI decision can be explained and understood, users are more likely to trust them. Building on this, Dennis (2024) argued that in auditing, trust in AI depends not only on its effectiveness in detecting fraud and anomalies but also on the continued role of human validation to ensure reliability.

While Trust Theory has been widely applied, it has also been critiqued for its limitations in certain contexts. Shapiro et al. (1992) argue that Trust Theory focuses too much on its positive aspects while overlooking potential negative consequences. They highlight that excessive trust can lead to exploitation and that research on trust should also consider its risks (Shapiro et al., 1992). Additionally, Gefen et al. (2003) argued that Trust Theory is limited when applied to technology, as it fails to account for critical aspects such as system reliability, security and users' perception of system's intentions. Thus, they claim that traditional Trust Theory was not designed to address the complexities and ethical concerns of digitalized environments (Gefen et al., 2003). Lastly, Dablain et al. (2024) emphasize the risks associated with AI trained on biased data, which can lead to biased results and distrust in AI systems.

Moreover, a key issue in applying Trust Theory to AI is the black-box nature of AI systems (Bathaee, 2018). Trust is built on the principles of ability, benevolence, and integrity, but these can be undermined when systems lack transparency (Mayer et al., 1995). In the case of generative AI, the reasoning behind its decisions is often inaccessible, which challenges auditors' ability to evaluate its benevolence and integrity, as the intentions and adherence to ethical standards are unclear (Bathaee, 2018; Doshi-Velez & Kim, 2017; Lipton, 2018). This lack of transparency can also compromise professional scepticism, as auditors may place too much trust in generative AI-generated insights without verifying the accuracy of the data (Lukyanenko et al., 2022). Additionally, ensuring that all AI decisions are ultimately reviewed and controlled by human professionals can prevent the blind trust in AI (Rahwan et al., 2019). Therefore, striking a balance between trust in AI and professional scepticism is crucial, as this balance will ensure that AI systems are trusted appropriately and not blindly (Gissel, 2018).

2.2.3 Comfort Theory

Comfort Theory was developed by Kolcaba and Kolcaba in the 1990s to explain how individuals seek relief, stability and a sense of empowerment in their environments (1991). The central premise of the theory is that comfort is a fundamental human need that influences well-being, performance, and overall satisfaction. Kolcaba (2001) identified three main types of comfort: *relief*, which involves the alleviation of specific discomforts; *ease*, referring to a general sense of calm, security and confidence; and *transcendence*, which enables individuals to perform beyond their usual capabilities. These types of comfort are experienced across four interrelated dimensions: physical, psychospiritual, environmental, and sociocultural (Kolcaba, 2003). Physical comfort relates to bodily needs and the absence of strain, while psychospiritual comfort includes emotional well-being, a sense of purpose, and confidence. Environmental comfort refers to the surrounding conditions—both physical and digital—that shape how individuals carry out their work. Sociocultural comfort involves interactions with others, including social support, shared norms, and a sense of belonging within a group. Comfort Theory has been applied in various organizational contexts to understand how employees respond to technological change and shifting work conditions, offering valuable insights into how emotional, cognitive, and relational factors affect adaptation (Almufadda & Almezeini, 2022; Jeong & Kim, 2019).

Comfort Theory has also been applied to the auditing profession, with Pentland (1993) introducing the concept. Pentland (1993) argued that auditors seek to reduce uncertainty by gathering sufficient evidence to build comfort in the numbers they report. Auditors rely on processes and routines to enhance their sense of comfort (Guénin-Paracini et al., 2014). When applied to auditing, Comfort Theory illustrates how auditors navigate the limitations of their profession and take necessary steps to reduce uncertainty (Duntara & Adhariani, 2019). This comfort reflects both a sense of assurance in their judgments and a stable psychological state amid uncertainty (Carrington & Catasús, 2007). The greater the uncertainty and risk, the less comfortable auditors feel. Rowe (2019) further explores this by examining how auditors seek comfort when dealing with uncertain estimates, showing that more evidence does not always lead to greater assurance, as excessive information can sometimes increase ambiguity rather than reduce it.

The application of Comfort Theory in auditing is particularly relevant in the context of technological advancements, especially artificial intelligence and automation. Auditors have historically relied on structured, rule-based manual processes to maintain professional judgement control over their work (Alles, 2015). Comfort Theory offers a lens to examine whether auditors experience relief, ease, or transcendence when working with AI-driven tools. In auditing, AI can provide relief by automating repetitive tasks such as data entry, risk assessment, and anomaly detection (Dowling & Leech, 2014). The ease auditors experience depends on their ability to trust AI-generated insights, understand its limitations, and integrate AI tools into their workflow without fear of errors or loss of professional judgment (Kend & Nguyen, 2020). Furthermore, generative AI has the potential to support transcendence by enabling auditors to focus on higher-value activities, such as fraud detection, advisory services, and strategic decision-making (Fedyk et al., 2022).

While Comfort Theory provides a useful framework for understanding auditors' responses to AI, it does not fully account for the role of human agency in shaping these responses (Appelbaum et al., 2017; Guénin-Paracini et al., 2014). Auditors are not passive recipients of technological change; rather, they actively engage with and interpret AI tools in ways that vary across individuals and organizations (Appelbaum et al., 2017). This variation explains why some auditors may experience AI as a source of relief and efficiency, while others perceive it as a disruption to their professional judgment and work routines (Carrington & Catasús, 2007). The level of comfort or discomfort auditors feel is therefore influenced not only by the nature of AI but also by their ability to adapt, exert control, and integrate these technologies into their work in a way that aligns with their professional values and expectations (Dowling & Leech, 2014).

Although originally developed to describe individual experiences, Kolcaba's model can be extended to professional environments where comfort influences adaptation and decision-making (2001). In such settings, comfort plays a dual role: while it reduces uncertainty and provides stability, it can also create resistance to change (Guénin-Paracini et al., 2014; Pentland, 1993). The theory has been criticized for its narrow scope, particularly its emphasis on immediate comfort without fully addressing how temporary discomfort may contribute to long-term growth and resilience (Kolcaba, 2001). As previously mentioned, auditors often find comfort in familiar procedures that structure their work and minimize risk. However,

overreliance on established routines may hinder adaptation to generative AI, which require new competencies and shifts in work routines (Carrington & Catasús, 2007). As generative AI becomes increasingly embedded in auditing, professionals must navigate the tension between the comfort of traditional methods and the demands of a data-driven future (Alles, 2015; Novizhilova et al., 2024).

These limitations become even more pronounced when applying Comfort Theory to high-stakes professional settings such as auditing, where critical thinking and scepticism are essential (Nelson, 2009). Auditing requires professionals to operate outside their comfort zones, questioning assumptions and exercising professional scepticism to ensure audit quality. The increasing integration of artificial intelligence and automation adds further complexity, requiring auditors to shift from familiar, rule-based processes toward more data-driven and technology-assisted approaches (Novizhilova et al., 2024). Many generative AI models operate as black-boxes, where the decision-making process is not fully understood, making it difficult for auditors to verify outputs (Bathaee, 2018). This lack of transparency can lead to ethical dilemmas, as auditors are responsible for ensuring the accuracy and integrity of financial assessments (Munoko et al., 2020).

From a Comfort Theory perspective, increased familiarity with generative AI tools may reduce uncertainty and improve auditors' confidence in their use (Carrington & Catasús, 2007). However, excessive comfort with automation can weaken professional scepticism by reducing critical engagement with AI-generated results (Hurtt et al., 2013). Research suggests that auditors may exert less effort and become less effective when reviewing AI-generated outputs compared to human-prepared work, highlighting the risk of over-reliance on technology (Emett et al., 2023). This overconfidence may lead to a reduced sense of responsibility in verifying results, which can negatively impact audit quality. As Harris (2017) warns, "*auditors should take care that they are not over relying on data analytics. As powerful as these tools are, or are expected to become, they nonetheless are not substitutes for the auditor's knowledge, judgment, and exercise of professional scepticism*". Similarly, studies by Emett et al. (2023) and Cao et al. (2022) emphasize that auditors' engagement with AI outputs may diminish if they rely too heavily on technology, potentially leading to decreased audit quality. To mitigate these risks, Parasuraman and Manzey (2010) argue that auditors should remain vigilant and maintain

professional scepticism, actively questioning AI-generated results, even as automation tools become more prevalent in the auditing process.

2.3 Concepts

2.3.1 Artificial intelligence

Artificial intelligence has been developed in several stages over time and has contributed to improvements across various sectors (Sandewall, 2014). One of the earliest significant developments was machine learning (ML), which enables AI systems to recognize patterns and perform automated tasks without human input (Haenlein & Kaplan, 2019). By allowing computers to carry out routine operations and basic control functions, machine learning has helped industries operate more efficiently (Sandewall, 2014). It can automate numerical processes such as data entry and calculations, significantly speeding up these tasks and reducing the need for human labour (Huang et al., 2022).

Furthermore, the development of computer vision—an AI technology capable of reading and interpreting visual data—further expanded automation potential (Chen & Williams, 2022). This allowed computers to read and process documents, enhancing their ability to support human work (Tyson & Zysman, 2022). As a result, work processes became more efficient across various fields, including accounting and auditing (Shao et al., 2022). In accounting, for example, computer vision enables the automated booking of invoices, requiring human input only for verification, thereby saving time and increasing accuracy (Azman et al., 2021).

These advancements have not only streamlined accounting processes but also transformed the auditing profession (Vasarhelyi et al., 2014). AI, particularly through computer vision, assists auditors by scanning reports and verifying data (Kokina & Davenport, 2017). Kokina and Davenport (2017) also highlight applications such as identifying duplicate invoices to detect fraud and automatically matching supporting documents for consistency. AI can also extract data and flag discrepancies between verification records and invoices, enabling auditors to review only the flagged items. These capabilities support more comprehensive and focused audits while reducing manual workload (Huang et al., 2022).

The latest upgrade in AI is generative AI, which is a type of artificial intelligence that can create new content, such as text, images, and structured data, by learning from large datasets

(Feuerriegel et al., 2024). Unlike traditional AI, which primarily follows rules or recognizes patterns in structured data, generative AI uses deep learning, particularly transformer models, to produce human-like outputs (Anica-Popa et al., 2024). The development of large-scale language models, such as OpenAI's GPT, has significantly expanded AI's ability to assist with complex tasks, including financial analysis and auditing (Zhao & Wang, 2024). This marks a shift from AI being used mainly for automation and prediction to a tool that can generate meaningful insights and support decision-making (Haenlein & Kaplan, 2019).

In auditing, AI has long been used for tasks like fraud detection, compliance checks, and data analysis (Issa et al., 2016). However, generative AI takes this further by helping auditors interpret financial data, summarize reports, and analyse large datasets using natural language processing (NLP) (Bible, 2023). Traditional AI models in auditing focus on identifying anomalies and ensuring compliance based on predefined rules (Kokina & Davenport, 2017), whereas generative AI supports judgment-based tasks by drafting audit reports, creating risk assessments, and simulating financial scenarios to assist in decision-making (Anica-Popa et al., 2024). This ability to generate context-aware insights makes AI particularly valuable in audit processes that involve judgment and qualitative evaluation.

Recent research highlights the increasing role of audit data analytics (ADA) in reshaping traditional audit methodologies (Kend & Nguyen, 2022). Kend and Nguyen (2022) emphasize that AI-driven audit analytics have significantly improved the efficiency and accuracy of audit processes in technologically advanced markets. By integrating AI with big data techniques, auditors can gain deeper insights into financial transactions, enhancing their ability to detect fraud and assess risk patterns more effectively (Kend & Nguyen, 2022). These advancements highlight the growing synergy between AI and auditing, reinforcing the need for auditors to develop technical competencies to leverage these tools effectively.

While generative AI offers significant advantages, it cannot fully replace traditional auditing tools or human judgment (Omoteso, 2012). Instead, it enhances auditors' ability to analyse large amounts of information efficiently. However, AI-generated outputs must be reviewed carefully, as they can sometimes be inaccurate or biased (Appelbaum et al., 2017). Since generative AI models rely on probabilistic methods to generate responses, they can sometimes produce misleading or fabricated information, a phenomenon known as AI "hallucination" (Goertzel,

2014). In auditing, where accuracy is critical, such errors could compromise the integrity of financial reports and lead to incorrect risk assessments. Another issue is bias in AI-generated content. AI systems are trained on historical data, which may contain biases that the model inadvertently learns and reproduces (Binns, 2018). In auditing, bias can lead to skewed financial analyses, misinterpretation of risk factors, or even reinforcement of pre-existing industry inequalities (Sutton et al., 2016). Auditors must remain observant when using AI tools to ensure that decisions are based on sound judgment rather than algorithmic bias.

Another technical limitation of AI—particularly generative models—is their lack of explainability. These systems often function as black-boxes, meaning the logic behind their outputs is not easily traceable or understood (Bathaee, 2018; Burrell, 2016). This creates challenges in auditing, where transparency and accountability are crucial. When auditors cannot explain how AI reached a particular conclusion, it becomes more difficult to verify findings, apply professional scepticism, or ensure compliance with regulatory standards.

Ethical concerns surrounding AI-based decision-making in auditing have also been raised. Lehner et al. (2022) argue that AI's role in audit decision-making introduces new ethical challenges, particularly in terms of accountability and transparency. As noted earlier, the black-box nature of many AI models complicates this further**,** potentially leading to compliance risks when auditors are unable to justify AI-generated conclusions (Bathaee, 2018; Burrell, 2016). Furthermore, Munoko, Brown-Liburd, and Vasarhelyi (2020) stress the need for ethical governance as AI technologies evolve faster than organizational controls. They highlight that regulatory bodies like the PCAOB and IAASB are working to establish updated standards to address the risks posed by emerging technologies (IAASB, 2018; PCAOB, 2018) This underscores the importance of continuous collaboration among auditors, regulators, and academics to ensure AI is used responsibly and in compliance with professional ethics.

However, while AI offers substantial benefits in terms of efficiency, there is a risk that it could undermine professional judgment if relied upon too heavily. Research indicates that auditors might become less engaged and more prone to overlooking critical details when reviewing AI-generated insights (Cao et al., 2022; Emett et al., 2023). This over-reliance on automation can lead to a reduction in the application of professional scepticism, which is essential in identifying potential errors or inconsistencies in financial data (Harris, 2017). Therefore, it is crucial that

auditors balance the use of AI with ongoing vigilance and critical evaluation to preserve the integrity of the audit process.

2.3.2 Audit Quality

Audit quality has been widely studied and examined, with DeAngelo (1981) defining it as the probability that an auditor detects misstatements and reports them. This definition underscores the importance of auditor's competence and independence in ensuring high-quality audits. The IAASB expands on this by emphasizing the auditor's role in providing reasonable assurance that financial statements comply with standards (IAASB, 2014). Francis (2011) further refines the definition by highlighting that audit quality is achieved when financial statements provide reliable information to stakeholders. Several key factors contribute to audit quality, including competence, independence, and structured audit processes (Francis, 2011). However, maintaining high audit quality is continuously challenged by client pressures, firm dependencies, and the growing integration of technological tools. While these factors play an essential role, this study highlights professional scepticism as the most crucial factor in safeguarding audit integrity (Al-Qatamin & Salleh, 2020). Without professional scepticism, auditors may overlook misstatements, rely too heavily on AI-generated outputs, or compromise their objectivity under client pressure (Kelly & Larres, 2025).

Competence ensures that auditors can detect misstatements by applying their knowledge of regulations, standards, and financial analysis (DeAngelo, 1981; Khairunnisa et al., 2023). Without competence, fraudulent financial statements could go undetected, leading to unreliable reporting (Francis, 2024). Independence is equally important, as auditors must remain objective and resist external influence (Tepalagul and Lin, 2015; Triantafillou, 2020). However, financial reliance on clients can threaten independence, making auditors hesitant to disclose misstatements (Mardijuwono & Subianto, 2018). Structured audit processes provide standardized guidelines to help auditors detect financial discrepancies while ensuring compliance with international standards (Francis, 2011; Owusu-Afriyie et al., 2024). Thus, audit processes are important for audit quality as they facilitate the work and create routines that can help the auditor with all other aspects of managing a high audit quality (Clout et al., 2013). In addition, professional scepticism—defined as a questioning mindset and a critical assessment of evidence—plays a key role in audit quality by ensuring that auditors actively challenge assumptions and do not accept information at face value (Kelly & Larres, 2025).

Despite these foundational elements, audit quality is continuously challenged by external pressures. One of the most significant risks arises from the tension between maintaining client relationships and ensuring auditor independence (Sulaiman, 2023). Since audit firms rely on clients for revenue, and they must maintain strong relationships to secure ongoing business (Sulaiman, 2023). This can create conflicts, as auditors may feel pressured to prioritize client satisfaction over objectivity, potentially overlooking misstatements (Ye et al., 2011). As audit firms become increasingly dependent on specific clients, their objectivity may be further compromised, ultimately reducing audit quality (Barkess et al., 2002; Sulaiman, 2023).

Additionally, the growing use of generative AI tools introduces new complexities. While generative AI has the potential to enhance fraud detection and efficiency (Nickell et al., 2023), there is a risk that auditors may become over-reliant on these tools, undermining their professional scepticism (Appelbaum et al., 2017). Insights produced by generative AI must be critically evaluated to prevent errors or misleading results (Goertzel, 2014). Therefore, auditors must maintain a balance between leveraging AI's capabilities and exercising their judgment to uphold independence and professional scepticism.

2.3.3 Professional Scepticism

Professional scepticism is a fundamental concept in auditing (Al-Qatamin & Salleh, 2020). It involves maintaining a questioning attitude, being alert to anomalies, and making critical assessments (Hurtt et al., 2013). To uphold professional scepticism, auditors must not accept information at face value but rather investigate its validity (Nelson, 2009). Key component of profession scepticism include neutrality, avoiding premature conclusions, and remaining objective until sufficient evidence is gathered (Al Shbail et al., 2024). Another important component is bias awareness, as recognizing cognitive biases allows auditors to counteract them (Gissel, 2018). Diligence is another key component, requiring auditors to conduct examinations of relevant documents and ensure they are independent and reliable (Gissel, 2018; Nelson, 2009). Lastly, it is crucial that auditors remain alert to inconsistencies, anomalies, and suspicious behaviour (Agustina et al., 2021). This ability is strengthened through experience as auditors develop a deeper understanding of fraud indicators.

By applying these principles, auditors enhance the reliability of their audits, as well as upholding ethical responsibilities (Nelson, 2009). Without professional scepticism, audit

integrity would be compromised, leading to undetected misstatements (Lord, 2018). Furthermore, professional scepticism ensures auditors' competence (Gissel, 2018) and helps maintain objectivity and independence, which are essential for audit quality (Adeoye et al., 2023). It is particularly important when it comes to risk-assessment and fraud detection (Payne & Ramsay, 2005). Through critical evaluation, professional scepticism raises awareness of inconsistencies that might be overlooked (Nelson, 2009). Maintaining a questioning mindset is therefore key to audit quality and keeping auditors vigilant (Hurtt, 2010).

Professional scepticism can be applied when working with AI (Kelly & Larres, 2025). As generative AI tools are increasingly used to generate financial figures, auditors must critically assess AI-generated data rather than accept it without careful evaluation (Adeoye et al., 2023; Puthukulam et al., 2021). This includes evaluating the reliability of AI outputs and questioning their validity (Lehner et al., 2022). Since generative AI systems may be trained on biased datasets, they can produce skewed results, making it crucial for auditors to understand the transparency of these systems and their decision-making processes (Appelbaum et al., 2017; Kokina & Davenport, 2017). Additionally, such systems may misclassify high-risk transactions as low-risk, potentially contradicting auditors' professional judgment (Appelbaum et al., 2017). To mitigate these risks, auditors must maintain integrity and apply their expertise to interpret AI-generated findings effectively. Given these challenges, professional scepticism plays a key role in ensuring audit quality and preventing blind reliance on generative AI, which could compromise financial integrity (Puthukulam et al., 2021).

3 Methodology

The third chapter will go through the methodology used in this study. This includes the methods, reasoning behind the chosen methods and the philosophy. It aims to justify the decisions and provide a guide for replication to further the trustworthiness of the study.

3.1 Research philosophy

Knowing the research philosophy is crucial for a study, as it can help guide the study to methodological points that strengthen the findings (Saunders et al., 2019). A well-defined research philosophy allows for a more focused research design, making the study more structured and coherent (Resnik, 2022). Furthermore, it ensures that the research question, method and findings align logically, contributing to the overall quality of the study (Saunders et al., 2019). Since the research philosophy influences the relationship between method and findings, it also affects the study's effectiveness and the relevance of its conclusions (Kuehn & Rohlfing, 2024). Therefore, defining the research philosophy provides a clear framework for conducting a well-founded study.

Ontology concerns the nature of reality and how it is perceived within the study (Easterby-Smith et al., 2021). In this research, a constructivist ontology is adopted, meaning that reality is seen as socially constructed rather than objectively determined (Shannon-Baker, 2016). Auditors' perceptions of AI in their work environment are shaped by individual experiences, professional backgrounds, and firm culture, making constructivism an appropriate ontological stance (Saunders et al., 2019). As generative AI transforms auditing processes, auditors may perceive this change differently based on their own trust in technology, professional expertise, and institutional pressures. This study acknowledges that multiple subjective realities exist regarding AI's role in auditing rather than assuming a single, objective truth.

Epistemology, the study of knowledge, influences how the research is conducted and how findings are interpreted (Otoo, 2020). Three common epistemological stances are positivism, interpretivism and pragmatism. This study primarily follows an interpretivist perspective, which emphasizes understanding human experiences and perspectives (Boucher, 2018).

Interpretivism seeks to explain how emotions and actions are interconnected (Resnik, 2022) and is commonly used in qualitative research, as it focuses on subjective phenomena (Lo et al., 2020). Interviews and observations are key methods within this stance, as they provide data based on individual experiences (Dodgson & Trotman, 2022).

This study adopts an interpretivist philosophy and a constructivist ontology to explore how generative AI influences auditors' comfort, focusing on subjective experiences and perceptions. Auditors' views are shaped by their unique professional environments, highlighting multiple subjective realities. The abductive approach aligns with this perspective, allowing for an iterative process between empirical observations and theoretical models. Instead of rigidly applying existing theories, abduction facilitates a dynamic exploration of how auditors adapt to AI-driven environments, refining insights as new data emerges. This flexibility enables the study to capture the evolving role of AI in auditing while ensuring theoretical relevance.

3.2 Research approach

Choosing an appropriate research approach is fundamental to ensuring the study's validity and alignment with its objectives. Research approaches primarily fall into deductive, inductive, and abductive reasoning, each offering different ways of linking theory and empirical data (Bell et al., 2019; Saunders et al., 2019). The choice of approach determines whether research starts from theoretical assumptions, builds theories from observations, or iterates between existing knowledge and emerging insights (Timmermans & Tavory, 2012).

A deductive approach is characterized by moving from established theories to empirical testing (Saunders et al., 2019). This method provides structured hypothesis testing and ensures logical consistency between theory and empirical observations (Blaikie, 2010). However, given the evolving nature of generative AI in auditing, a purely deductive approach may overlook emerging perspectives and complexities that are not yet fully captured by existing theories (Fedyk et al., 2022). Conversely, an inductive approach starts with data collection and derives theories from observed patterns (Saunders et al., 2019). Instead of testing predefined hypotheses, this approach allows for exploratory research, particularly useful when studying new or underexplored phenomena (Creswell, 2014). While inductive reasoning enables a deep understanding of auditors' perspectives, it may not sufficiently connect findings to existing theoretical frameworks, limiting its explanatory power (Denscombe, 2017).

An abductive approach provides a balanced alternative, iterating between theory and empirical data to refine explanations and explore complex phenomena (Morgan, 2007). Abduction begins with an observation—such as the uncertainty auditors experience when verifying AI-generated financial data—and seeks the most plausible explanation by integrating existing theories and new insights (Timmermans & Tavory, 2012). This recurrent process aligns well with studies in organizational and behavioural research, where institutional pressures, trust, and professional scepticism interact in unpredictable ways (Law & Shen, 2024).

Given the objectives of this study, an abductive approach is the most appropriate. Generative AI's role in auditing is still evolving, and existing theories—such as Comfort Theory, Trust Theory, and Institutional Theory—provide useful yet incomplete explanations of how auditors navigate generative AI integration. By moving between theoretical models and empirical findings, this approach allows for a contextually grounded exploration of how auditors adapt to generative AI-driven auditing environments (Jeong & Kim, 2019). Furthermore, abduction accommodates the uncertainty and variation in how different auditors perceive AI, making it well-suited for a study that aims to capture dynamic and evolving professional experiences (Saunders et al., 2019; Timmermans & Tavory, 2012). It allows the study to bridge the gap between AI's theoretical potential and its practical implications in auditing, iterating between theoretical expectations and empirical findings (Law & Shen, 2024; Morgan, 2007).

Additionally, the interviews were conducted through an ongoing, back-and-forth process between the researcher and participants. This iterative approach aligns with the inductive reasoning, where insights from earlier interviews informed subsequent rounds, enabling the study to explore auditors' perceptions of AI from multiple perspectives and adapt the data collection as new patterns emerge.

3.3 Research methodology

This study adopts a qualitative research approach, as it aims to explore auditors' experiences and perceptions regarding the integration of generative AI in auditing. Qualitative research is particularly suitable for understanding complex social and professional phenomena, as it provides rich, in-depth insights into participants' thoughts, experiences, and interpretations (Antwi & Hamza, 2015). Unlike quantitative research, which relies on numerical data and

statistical analysis, qualitative research focuses on gathering descriptive and contextualized information through open-ended inquiry (Saunders et al., 2019).

A semi-structured interview method has been selected as the primary data collection technique. This approach allows for flexibility in exploring auditors' perspectives while maintaining a structured framework that ensures consistency across interviews (Johnson & Onwuegbuzie, 2004). Semi-structured interviews provide the opportunity for follow-up questions and deeper discussions, enabling researchers to capture nuances in auditors' comfort levels, trust in outputs produced by generative AI, and responses to institutional pressures (Saunders et al., 2012). Given that AI generative integration in auditing is still evolving, this method is particularly valuable in uncovering emerging challenges and contextual factors that may not be captured through standardized survey methods (Bell et al., 2019).

However, qualitative research also presents certain challenges. Since qualitative data is subjective and context-dependent, findings may be less generalizable compared to quantitative studies that rely on larger sample sizes and statistical validation (Creswell, 2014). Additionally, analysing qualitative data requires careful interpretation, as researchers must categorize responses, identify themes, and ensure objectivity in the analysis (Choy, 2014). To mitigate potential biases, both researchers will be involved in data collection and transcription to enhance reliability.

The choice of a qualitative approach aligns with the study's abductive research design, which emphasizes iterative refinement between theory and empirical findings (Bell et al., 2019). As auditors' experiences with generative AI are shaped by their professional context, institutional environment, and individual attitudes, a qualitative approach enables an in-depth exploration of these evolving dynamics. Through abductive reasoning, the study will continuously refine its theoretical interpretations as new patterns and insights emerge, supporting a more comprehensive understanding of how generative AI is reshaping the auditing profession.

3.3.1 Data collection

For this study, the primary data was collected through semi-structured interviews to explore auditors' experiences and perceptions of generative AI in auditing. A total of 10 auditors from various audit firms were interviewed, providing insights into how they integrate generative AI

into their work and their comfort levels with AI-generated financial data. The interviews were conducted in one round, with each participant providing valuable input on different aspects of AI adoption, trust, and job security within their firms. A follow-up interview of about 10 minutes was scheduled only if deemed necessary for clarifying or expanding upon key points. This ensured that the findings are comprehensive and well-rounded (Saunders et al., 2012).

Semi-structured interviews were chosen for their flexibility, allowing the interviewer to ask predetermined questions while also exploring emerging themes that arose during the conversation (Saunders et al., 2019). This approach enabled the researchers to delve deeper into specific issues such as the trust auditors place in generative AI systems and how these systems impact their daily tasks and decision-making processes. While the interview guide ensured consistency across the interviews, the flexibility of semi-structured interviews allowed for additional questions to be asked based on individual responses, thereby enriching the data (Turner, 2010).

The interviews were conducted in a conversational manner, where participants were encouraged to share their thoughts freely, fostering a deeper understanding of their personal experiences and opinions about generative AI in auditing (Kallio et al., 2016). This method is particularly effective for qualitative studies, as it provides insight into participants' individual viewpoints and helps capture the complexity of their experiences (Bell et al., 2019). The interview guide, developed in advance, covered several key themes such as the auditors' background, their use of generative AI in auditing, perceptions of trust in AI-generated data, and concerns about job security in the context of AI integration.

While semi-structured interviews are beneficial for obtaining rich, detailed data, they also present challenges (Adams W. C., 2015). The method is time-consuming, requiring skilled interviewers to manage the conversation and ensure that the data collected remains relevant to the research question (Easterby-Smith, 2018). Additionally, the subjective nature of qualitative data analysis requires careful interpretation to avoid bias and to ensure that themes are accurately identified and categorized (Choy, 2014). To mitigate these challenges, both researchers were involved in the data collection and transcription process, and participants had the opportunity to review their responses for accuracy and completeness (Harvey-Jordan & Long, 2001). Additionally, during the interview, active listening, managing silences, and

maintaining a non-judgmental attitude were crucial to encourage open discussion and enhance the depth and reliability of the data (Adams, 2010).

3.3.2 Interview guide

The development of the interview guide followed the decision to use semi-structured interviews as the primary data collection method (Easterby-Smith, 2018). Establishing a comprehensive interview guide involves careful consideration and time to formulate relevant and informed questions. According to Qu and Dumay (2011), the researchers must have a thorough understanding of the study's subject matter to ensure that the questions align with the research focus. This insight, gained from the literature review, enabled us to design a guide that effectively addresses the key aspects of generative AI's impact on auditing (Qu & Dumay, 2011).

A crucial aspect of the interview guide is the formulation of questions in a way that makes them clear and accessible to the participant (Easterby-Smith, 2018). Questions that are perceived as irrelevant, difficult, or inappropriate can lead to disengagement, which negatively impacts the quality of the interview. For this reason, the interview questions were carefully constructed to ensure their relevance to the study and their appropriateness for the participants (Turner, 2010). We paid particular attention to making sure the questions felt relevant to the auditors' experiences, thus encouraging open and meaningful responses.

Incorporating open-ended questions is another important feature of the guide (Hammarberg et al., 2016). These types of questions allow participants to provide detailed and thoughtful responses, offering rich qualitative data that structured questions may not uncover. Open-ended questions also encourage participants to reflect on their experiences and share insights in their own words, facilitating a deeper understanding of their perceptions and attitudes toward generative AI in auditing (Lim, 2024).

In this study, the interview guide is divided into sections, each corresponding to a specific theme uncovered in the literature review. This structure ensures that the interview remains focused on the research questions while also providing flexibility to explore new insights that may arise (Bell et al., 2019). The guide begins with a section on background and experience, allowing participants to introduce themselves and provide context regarding their role and experience with AI in auditing (Creswell, 2014). This is followed by questions exploring the participants'

use of generative AI in auditing and accounting, their comfort with AI-generated financial data, and their perceptions of trust, and institutional pressures related to AI adoption.

Furthermore, the guide includes a section dedicated to job security, examining how generative AI influences career progression and potential threats to the auditing profession. The final part of the interview guide provides an opportunity for participants to offer additional thoughts or experiences that may not have been covered by the questions, ensuring that their views are fully expressed. The interview guides can be found in English in *Appendix 1 & 2 (revised and original)* and in Swedish in *Appendix 3 & 4 (revised and original)*.

As the interviews progressed, the interview guide was iteratively refined based on participants' responses and contextual factors. For example, we found that auditors from smaller firms often had limited experience with generative AI tools in their workflows. In such cases, certain questions—such as "How comfortable are you using generative AI in your daily tasks?"—were rephrased to instead explore hypothetical perspectives, like "How comfortable do you think you would be using generative AI in your daily work?" This adaptation ensured the relevance of the questions across diverse participant backgrounds. Additionally, after conducting the first few interviews, we identified questions that were either repetitive or did not yield new insights. These were adjusted or removed in subsequent interviews to streamline the process and maintain participant engagement. This adaptive approach ensured that the interviews remained meaningful, context-sensitive, and aligned with the overall research objectives. This adaptive approach reflects the abductive and iterative nature of qualitative research, where data collection and theory development inform each other continuously (Saunders et al., 2012). The final interview guide can be found in English in *Appendix 1* and in Swedish in *Appendix 3*.

3.3.3 Sampling

This study used purposive sampling to select auditors from Sweden. Purposive sampling is a non-probability sampling method that allows researchers to select participants based on specific criteria that are relevant to the research question (Easterby-Smith et al., 2021). Since the aim of this study is to understand how auditors' experiences and perceptions of generative AI vary across different contexts, purposive sampling was deemed appropriate. The sample was not randomly selected, as we wanted to gain in-depth insights into the specific experiences of auditors with generative AI rather than to obtain a representative sample of the broader auditor

population (Saunders et al., 2012). In line with the research objectives, the sample was strategically selected to include auditors from both large and small firms, as well as both senior and junior auditors, to capture diverse perspectives on the topic (Bell et al., 2019). Auditors from different organizational positions, such as assistants and seniors, may have differing views and experiences with generative AI implementation in their work. Senior auditors often have more exposure to strategic decision-making regarding generative AI, whereas junior auditors may be more involved in the use of generative AI tools in day-to-day tasks. Including both groups ensures a comprehensive understanding of the various ways generative AI is shaping the auditing profession across different experience levels.

While alternative non-probability sampling methods, such as snowball or self-selection sampling, were considered, purposive sampling was preferred for its strategic focus. Snowball sampling, where participants refer others to the study, was avoided to ensure that auditors from a diverse range of firms and geographic locations were included (Emerson, 2015). Self-selection sampling, where participants volunteer to participate, was also considered (Heckman, 1990). However, this method was not suitable as we did not find an appropriate channel to publicize the study and invite auditors to express interest. As a result, we chose purposive sampling, which allowed the research to specifically target auditors who could offer the most relevant and varied insights based on their professional roles, experiences, and geographic location (Bell et al., 2019).

Moreover, the firms selected for this study represent a range of generative AI adoption stages. Some firms may have already implemented generative AI-driven tools extensively, while others are still in the early stages of incorporating generative AI into their auditing processes. By selecting auditors from firms at different stages of generative AI adoption, this study gains insights into how the level of generative AI integration within a firm impacts auditors' perceptions and comfort with the technology (Bell et al., 2019). This approach ensures that the study captures the evolving nature of generative AI adoption and its effects on auditors' professional roles.

For this study, interviews were conducted with 10 auditors, including both junior and senior auditors from a variety of firms. A table of the interviewees can be found in *Appendix* 5. This number of interviews was chosen to ensure that the study could capture a wide range of

experiences and perspectives, while still allowing for in-depth exploration of the research questions. According to Saunders et al. (2012), the appropriate sample size in qualitative research depends on the research goals and the richness of the data collected. Given the subjective nature of the research topic and the exploratory nature of the study, 10 interviews provided enough diverse perspectives without overwhelming the analysis process. This sample size also allowed for a thorough examination of the evolving relationship between auditors and generative AI, as patterns and themes emerged across the interviews.

3.3.4 Interviews

In total, 10 interviews were conducted with auditors in Sweden for this study. Of these, three interview was conducted in person, and the remaining seven interviews were conducted remotely using Microsoft Teams. The choice of conducting both in-person and remote interviews was influenced by the nature of the participants' availability and convenience, while also aiming to maintain a natural and authentic conversation (Saunders et al., 2012).

The in-person interviews allowed for more direct and engaging interactions, which can be beneficial when addressing complex topics and encouraging open discussion (Easterby-Smith et al., 2021). Of the three in-person interviews, two were conducted with senior authorized auditors, and one was conducted with an associate-level auditor. All participants provided valuable insights based on their experiences with generative AI adoption. Conducting the interviews face-to-face fostered a more open and comfortable atmosphere, encouraging participants to share detailed reflections on their experiences (Saunders et al., 2012). This was particularly important given the seniority and authorization status of two participants, whose perspectives were essential to understanding the broader organizational and strategic implications of generative AI integration.

For the seven remote interviews, Microsoft Teams was chosen as the platform for its reliability, ease of use, and excellent audio and video quality, which ensured the smooth flow of conversation. Remote interviews provide flexibility for both the researcher and participants, which was particularly relevant given the participants’ varying schedules and locations across Sweden (Roberts et al., 2025). The remote setup also helped ensure the participants were in a comfortable environment, minimizing logistical challenges often associated with in-person interviews (Dodds & Hess, 2020).

One consideration in conducting interviews is the potential for interview bias, where a researcher's perspectives or actions influence the responses of participants (Easterby-Smith et al., 2021). To minimize this risk, we employed strategies such as encouraging participants to elaborate on their answers by asking follow-up questions, such as "Could you tell us more about that?" or by rephrasing questions to ensure clarity and avoid leading responses (Bell et al., 2022). Additionally, we paid attention to tone, pauses, and hesitations, as these can provide deeper insight into participants' thoughts and emotions (King & Brooks, 2017). This approach helped us interpret responses more accurately while reducing the risk of influencing participants' answers.

To enhance the efficiency of data collection, all interviews were audio-recorded with the consent of the participants. Audio-recording interviews is beneficial as it allows the researcher to focus on the conversation without the need to take extensive notes, ensuring a more natural interaction (Saunders et al., 2012). However, despite the recording, we also took handwritten notes during each interview to capture immediate impressions, non-verbal cues, or any points that could be emphasized in the analysis (Easterby-Smith et al., 2021). This also served as a backup in case the audio recording encountered any issues.

For transcription, we utilized the automatic transcription feature in Microsoft Teams for the online interviews, which transcribed the conversations in real time. For the in-person interviews, we used the Cockatoo transcription tool. Although these tools expedited the transcription process, the automatically generated transcripts were not always perfectly accurate (Eftekhari, 2024). To ensure the highest level of accuracy, the transcriptions were reviewed twice by both researchers. Each of us listened to the recordings separately, identifying any discrepancies or errors in the transcriptions. Once we had individually made the necessary corrections, we came together to compare our notes and ensure consensus on the changes made. This collaborative review process helped minimize the risk of errors and biases, ensuring that the transcriptions accurately reflected the content of the interviews (Bell et al., 2022; Eftekhari, 2024).

Furthermore, we chose to conduct the interviews in Swedish, as we are based in Sweden and were speaking with Swedish participants. This decision was made to ensure that the participants felt as comfortable as possible during the interviews and could express themselves in the

language they are most proficient in (Chen & Boore, 2010). According to Chang et al. (1999), ensuring linguistic equivalence is crucial when translating research instruments to maintain the same meaning and context across languages. By conducting the interviews in Swedish, we aimed to minimize any language barriers that could hinder the richness and depth of the responses (Temple & Young, 2004). This choice also allowed the participants to convey their experiences and insights more naturally, without the constraints of translating technical terms or complex ideas into a second language (Temple & Young, 2004). After the transcriptions were finalized, they were translated from Swedish to English to facilitate analysis. Ensuring the accuracy of the translation was critical for maintaining the integrity of the data, and the translation process was done collaboratively to ensure consistency and precision in the interpretation (Chen & Boore, 2010).

3.3.5 Data analysis

Analysing qualitative data requires a structured approach to ensure coherence and transparency in how insights are derived (Saunders et al., 2012). In this study, we employed thematic analysis, a widely used method for identifying and interpreting patterns within qualitative data (Braun & Clarke, 2006). Thematic analysis allows for flexibility in analysing textual data while maintaining a clear structure that ensures findings are systematically organized (Bell et al., 2019). Since our study follows an abductive research approach, the analysis was conducted iteratively, meaning we moved back and forth between the data and relevant literature to refine our themes and interpretations (Easterby-Smith et al., 2021). This iterative approach ensured that our findings were continuously validated against theoretical concepts, allowing us to develop well-grounded insights.

To analyse the interviews, we started by looking for repeated topics and phrases throughout the interviews, a strategy recommended by Bell et al. (2019) when identifying themes. These repetitions guided us in finding categories and themes that were central to participants' responses. We then coded the data by assigning a short label to each meaningful sentence or segment of text. This coding process broke down the large amounts of data into smaller, manageable units that captured key ideas. It helped us identify both commonalities and differences in how participants discussed generative AI in auditing. To maintain confidentiality

while keeping track of responses, we assigned each participant an identifier: the first participant was labelled P1, the second P2, and so on.

After coding, we identified themes by grouping related codes together. For instance, codes such as P4: Using generative AI for simple analytical tasks and P1: Using generative AI to scan large datasets for discrepancies were categorized under the broader theme Usage of generative AI. To ensure a structured and transparent organization of these themes, we used colour coding, visually distinguishing different categories. This step enhanced the clarity of the analysis and allowed for easier comparison of themes across participants. Initially, both researchers conducted independent coding to identify key themes before reviewing and finalizing the classifications together. This process not only ensured consistency and reliability but also encouraged discussions of different interpretations, reducing the risk of researcher bias. To gain a more comprehensive understanding of the data, related themes were further organized into aggregated dimensions, such as generative AI integration. These dimensions provided a higher-level framework that helped reveal overarching patterns and interconnections between different themes. This structuring allowed us to analyse how factors such as generative AI usage, trust, and institutional influences interact in the auditing field. A more detailed version of the full thematic analysis is available in *Appendix 6*.

The choice of thematic analysis was motivated by its ability to structure complex qualitative data while maintaining flexibility in interpretation (Braun & Clarke, 2006). This method was particularly suitable for our study, as it enabled us to uncover both expected and unexpected themes in the data, aligning with the abductive nature of our research. The abductive approach emphasizes plausible reasoning, meaning that findings emerge through a continuous interplay between empirical observations and theoretical concepts (Easterby-Smith et al., 2021). Instead of merely confirming existing theories or developing entirely new ones, we sought to refine our understanding of generative AI adoption in auditing by iteratively comparing our data with prior research.

3.4 Ethical considerations

Throughout this study, ethical principles were carefully considered to ensure participants' rights were respected and the integrity of the research was maintained. One of the primary ethical

considerations was obtaining informed consent (Bell et al., 2022). Prior to the interviews, participants were thoroughly informed about the study's objectives, the nature of the questions, and how the data would be utilized (Ormandy & Brown, 2017). It was made clear that their participation was voluntary, and they could withdraw at any point without any repercussions. This transparency helped foster trust and encouraged participants to share their true opinions.

Given the focus of the study on participants' comfort with generative AI, it was essential that they felt secure in expressing their thoughts without any external pressure or fear of judgment (Millar, 2006). This openness allowed participants to offer honest insights into their perspectives on generative AI, rather than providing responses they felt were expected. We took steps to ensure a neutral and non-intimidating atmosphere, which encouraged candidness and honesty during the interviews.

Confidentiality was another central ethical consideration (O'Neil, 2016). The identities of the participants were kept private to maintain confidentiality throughout the data analysis and reporting process. All personal data and sensitive information were stored using cloud services provided by Jönköping University, with access strictly limited to the research team. To ensure compliance with data protection regulations, we followed the guidelines for data handling provided by Jönköping University, as well as the General Data Protection Regulation (GDPR). Once the study is published, all data will be deleted, adhering to GDPR's principles of data retention and removal. Additionally, the transcription of interviews was conducted via Microsoft Teams and Cockatoo. We ensured that Microsoft Teams adhered to GDPR regulations, and according to Cockatoo, no third parties have access to the information processed through their platform (Cockatoo.com, n.d).

Moreover, it was important to uphold transparency throughout the study to avoid any biases that might compromise the findings. As transparency is key to maintaining ethical standards, we made sure to clearly communicate the study's goals and ensure neutrality in our approach (Eubanks, 2018). We carefully designed interview questions to avoid leading participants and encouraged open-ended responses to capture genuine opinions. This approach ensured that the participants' perspectives were accurately represented and that the research process remained objective.

3.5 Research quality

When assessing research quality, trustworthiness plays a crucial role in evaluating qualitative research (Lincoln & Guba, 1985). Trustworthiness can be broken down into four key elements—credibility, transferability, dependability, and confirmability—which are essential for a comprehensive evaluation of the research (Bell et al., 2022).

3.5.1 Credibility

Credibility is crucial in ensuring the trustworthiness of the findings, particularly in qualitative research, as it ensures the data accurately reflects the participants' lived experiences and is believable within the research context (Bell et al., 2022). In this study, the use of semi-structured interviews as the primary data collection method places emphasis on obtaining in-depth insights rather than statistical representativeness. While qualitative research does not aim for large samples, concerns about representativeness can still arise. To address this, purposive sampling was used to include a diverse range of participants with varying roles and experiences related to generative AI in auditing, thereby enhancing the credibility and richness of the findings (Bell et al., 2019). This strategy ensured a targeted selection of auditors from firms at different stages of generative AI adoption, and from various organizational levels, including senior and junior auditors. As Easterby-Smith (2018) suggests, this approach guarantees that the chosen participants have relevant experience and knowledge, which enhances the relevance and depth of the data. The sampling process for this study included auditors from both small and large firms, capturing a broad range of experiences with generative AI integration and its impacts.

Including multiple perspectives, secondary data, and existing theory enhances research credibility by enabling cross-validation through triangulation (Patton, 1999). Triangulation helps confirm if similar results emerge from various data sources, strengthening the validity of the findings. However, our study revealed discrepancies between existing literature and empirical results. For example, while literature suggests that auditors may exert less effort when reviewing outputs produced by generative AI (Emett et al., 2023), our findings indicate that auditors apply a consistent level of effort regardless of whether the outputs are generated by generative AI or humans. Patton (1999) notes that deviations from existing theory do not reduce credibility but offer deeper insights into the relationships between elements. Triangulation was

also employed during the coding process of the interview data to ensure a thorough analysis and strengthen the validity of our findings.

To ensure credibility, the study employed strategies such as member checking (Bell et al, 2022). After initial analysis, the draft findings were sent back to participants for feedback to confirm that the interpretations were accurate and representative of their experiences. This approach aligns with Bell et al. (2022), who argue that member checking helps ensure the validity of qualitative research by involving participants in the verification process. Moreover, the collaborative nature of the data analysis process further strengthened the credibility of the study. As discussed by Bell et al. (2019), collaboration between researchers during the coding and thematic analysis process reduces the likelihood of individual biases affecting the findings. By working together throughout the analysis phase, the researchers were able to cross-check their interpretations, discuss emerging themes, and ensure a more holistic understanding of the data, minimizing the risk of overlooking important insights.

3.5.2 Transferability

Transferability in qualitative research refers to the degree to which findings can be applied to other settings, organizations, or contexts (Curtin & Fossey, 2007). Unlike quantitative research, which often aims for generalizability, qualitative research focuses on providing deep insights into specific contexts. Given the focus of this study on the impact of generative AI adoption in auditing, particularly in Swedish firms, transferability is not about making broad generalizations but rather about offering sufficient contextual details for readers to assess the applicability of the findings to similar contexts.

To enhance transferability, the study provides a detailed explanation of the context in which the data was collected, including the roles of the interview participants and whether they worked at small or large audit firms. This information, as outlined in *Appendix* 5, enables readers to assess whether the findings may be relevant to other firms or sectors also navigating generative AI adoption (Bell et al., 2022). Transparency regarding the case companies and participant backgrounds supports a more informed judgment about the applicability of the study's insights to different organizational contexts or industries.

Additionally, the study's abductive research approach supports transferability by allowing a dynamic relationship between empirical findings and existing theory. As Saunders et al. (2012) explain, an abductive approach enables ongoing comparisons between theory and empirical data, broadening the theoretical significance of the findings. This constant movement between data and theory strengthens the transferability of the study, as it connects the findings to broader theoretical frameworks that may be relevant to other industries or organizational contexts, thus allowing readers to assess whether the findings could be applicable to their own situations.

This study is also grounded in a constructivist ontology and interpretivist epistemology, focusing on understanding how individuals interpret their experiences with generative AI adoption (Boucher, 2018; Shannon-Baker, 2016). These approaches emphasize the context-specific nature of the findings, as they are rooted in the participants' subjective experiences. The focus is not on generalizability but on offering insights into how specific contexts, such as those found in the Swedish auditing industry, influence the understanding and application of generative AI.

3.5.3 Dependability

Dependability refers to the consistency and reliability of the research process, specifically whether the study can be replicated with similar results (Bell et al., 2022). In qualitative research, dependability is achieved through clear documentation and transparency in the research process, allowing others to follow the steps taken and assess the suitability of the methods used (Guba, 1981). For this study, dependability was ensured through a detailed presentation of the research process, including the data collection and analysis methods, which were thoroughly explained in the methodology section.

To establish dependability, the research employed stepwise replication, where both researchers individually analysed the data to see if they arrived at the same conclusions. This approach is recommended by Anney (2014) as it helps to ensure that the findings are consistent and not influenced by personal biases. Throughout the study, the researchers conducted their own individual analyses, after which they compared their findings and discussed any discrepancies. Additionally, the study's collaborative approach to data coding further enhanced dependability. The researchers worked together during the coding process to ensure that no important themes or insights were overlooked. As Bell et al. (2022) note, collaboration in the analysis phase

reduces the risk of individual biases and ensures that the findings are robust and consistent across different interpretations. In cases where the researchers disagreed on specific interpretations, they engaged in detailed discussions to reach a consensus. This collaborative approach to data analysis increases the dependability of the findings and helps ensure that the conclusions drawn from the data are reliable.

Moreover, peer examination was another key strategy used to enhance dependability. The study was presented at several research seminars where the researchers received feedback from neutral colleagues, allowing them to critically evaluate their methodology and findings. This peer review process, as suggested by Anney (2014), provides an additional layer of scrutiny and ensures that the study's findings and methods can withstand external critique. These discussions helped identify potential areas for improvement and ensured that the research process was adequately detailed to allow for replication.

3.5.4 Confirmability

Confirmability is linked to objectivity and refers to ensuring that the researchers' personal biases and beliefs do not influence the outcomes of the study (Bell et al., 2022). To mitigate the risk of bias in this study, we took several steps to ensure the data analysis process remained as objective as possible. Since both researchers were not always present during each interview, all interviews were audio-recorded with the participants' consent, and the recordings were thoroughly reviewed by both researchers afterward. This collaborative review process allowed us to independently analyse the data and discuss our individual interpretations, ensuring that no single perspective disproportionately influenced the conclusions.

In addition to this, we engaged in regular discussions throughout the data collection and analysis process. These discussions allowed us to reflect on our personal biases and assumptions, making us more aware of how our backgrounds might shape our interpretations. This approach is consistent with Guba's (1981) concept of confirmability, which emphasizes the importance of incorporating multiple perspectives during data interpretation to enhance objectivity.

Furthermore, we followed Anney's (2014) strategy of reflexive practice by engaging in critical discussions about our study. While we did not maintain a formal reflexive journal, these ongoing conversations enabled us to acknowledge and address any potential biases and

assumptions, ensuring that our conclusions were rooted in the data rather than personal perspectives. By reviewing the data collaboratively and reflecting on our biases, we were able to enhance the confirmability of our findings, ensuring a more objective and balanced analysis.

3.5.5 Usage of AI

AI has been utilized in this study as a supplementary tool to enhance efficiency, particularly in structuring sections and identifying key areas of focus. The primary use of AI, specifically ChatGPT, was to provide guidance on organizing information and determining what theoretical aspects should be covered. However, AI did not contribute to generating original ideas, conducting analyses, or interpreting findings.

To ensure the study's trustworthiness, all content was derived from academic sources, and AI was not used as a substitute for critical thinking or academic rigor. Additionally, Primo's AI-powered research assistance was employed to locate relevant literature, ensuring that no key sources were overlooked. However, all sources were thoroughly reviewed and evaluated by the researchers to maintain academic integrity.

Furthermore, Microsoft Teams' AI-based transcription function was used to transcribe the interviews. However, recognizing that automatic transcription is not entirely reliable and may contain errors, the researchers carefully reviewed all recorded material to verify accuracy and ensure that no important details were misinterpreted or omitted. Additionally, Cockatoo, a transcription tool, was employed for certain interviews, with the same level of scrutiny applied to the transcripts for accuracy. This additional step helped maintain the trustworthiness and accuracy of the empirical data. Therefore, the use of AI in this study did not compromise its credibility or reliability but served as a supporting tool to enhance the research process.

4 Findings & Discussion

The fourth chapter presents the findings through an integrated discussion. It aims to analyse and interpret the data in a clear and structured manner, drawing on the theoretical perspectives outlined in chapter two. In this chapter, the term "AI" refers specifically to generative AI, unless otherwise specified.

4.1 Balancing Innovation and Integrity: How Generative AI Integration Reshapes Auditors' Comfort

Throughout the interviews, auditors shared diverse reflections on the integration of AI into audit practice, revealing how this transformation is mediated by their usage patterns, human judgment, and perceptions of quality. These insights formed the aggregated dimension of generative AI integration, which captures how auditors experience, respond to, and shape the role of generative AI in their professional environments, as well as how firms integrate generative AI into existing systems and workflow to align with regulatory expectations and professional practices. The themes— generative AI usage, human factor, and generative AI quality—do not stand alone, but interact to define how meaningfully generative AI is embedded in daily audit tasks. This section analyses these interrelated themes to understand how integration is not just technical implementation, but an ongoing process of negotiation between tools, people, and institutional expectations.

Auditors' experiences with artificial intelligence reveal a profession negotiating both the demands of technological transformation and the preservation of core professional values. Institutional pressures—coercive, mimetic, and normative—have played a central role in shaping how AI is integrated within audit firms (DiMaggio & Powell, 1983). These pressures are not just organizational constraints but cultural forces that signal how auditors ought to respond to innovation. Collectively, these institutional dynamics influence not only whether AI is adopted, but how it is interpreted by those expected to use it.

While scepticism existed, many participants believed their firms are adopting AI because it is perceived as a constructive and forward-looking development. As one auditor put it:

"… but I'd say it's because it's positive"

This optimistic framing reflects not only a growing trust in the potential of AI but also a willingness to adapt to the evolving demands of the profession (Kelly & Larres, 2025). From this perspective, AI is not a threat but a catalyst for transformation—introducing new possibilities while preserving core professional functions also provides a sense of strategic comfort, as it aligns with the profession's long-term direction.

Yet, beneath this optimism lies a critical nuance: while AI tools are increasingly available, their integration remains uneven. As one participant admitted:

"There are so many AI tools within the company, but I only know a small part of them. I would have liked a walkthrough of how they work and how they can be used in auditing."

This statement points to a superficial form of integration. As Meyer and Rowan (1977) describe, symbolic adoption occurs when tools are introduced to fulfil external legitimacy pressures but are not fully embedded into daily practices. This superficial integration created a disconnect between organizational ambition and individual comfort.

Comfort emerges as a key mediator in this process. Kolcaba's (2003) framework of comfort—shaped by physical, psychospiritual, environmental, and sociocultural domains—offers insight into how auditors navigate technological change. When firms provide insufficient training or fail to connect tools to meaningful audit tasks, uncertainty and discomfort take over (Nickel et al., 2023). As one participant explained:

" I would need training on how to ask questions and how to use AI in the best way to get the most out of it… That would make me feel more confident in trusting the system."

This statement highlights how comfort and trust are interlinked, confidence in AI use depends not only on its functionality, but on how well the surrounding structures support its implementation (Nickel et al., 2023). In this context, trust is not placed in the technology itself, but in the institutional infrastructure that enables its safe and effective use (Appelbaum et al.,

2017). Larger firms, in particular, were seen to foster higher levels of trust due to their ability to develop, validate, and internalize AI tools. As one participant from a large firm noted:

"We have developed an AI assistant called …. It works similarly to ChatGPT but is internally developed for us."

This highlights a broader pattern: trust and perceived quality in AI adoption are strongly tied to organizational credibility and internal capacity. Larger firms are often seen as more capable of implementing AI tools in a trustworthy and professionally rigorous manner (Seethamraju & Hecimovic, 2023). This perception is rooted not only in technical capacity but also in the ability to validate and test innovations in alignment with evolving professional standards (IAASB, 2014; Francis, 2011). These conditions enhance auditors' confidence in the quality and reliability of AI outputs (Appelbaum et al., 2017; Goertzel, 2014). In contrast, participants from smaller firms emphasized that they often rely on publicly available tools and face greater challenges in terms of integration, training support, and institutional validation. This discrepancy reinforces a two-tiered audit landscape (Munoko et al., 2020; Zavodna et al., 2024), where trust in AI is shaped less by the technology itself and more by the institutional credibility and resources of those deploying it.

These dynamics also influenced how auditors interact with AI on a day-to-day basis. Several participants described using the tools in exploratory ways, testing their capabilities and drawing on them for informal input rather than final judgment. As one participant put it:

"But I think we benefit from it because everyone finds it fun—especially using it as a bit of a sounding board."

The way auditors frame AI as a "sounding board" rather than a decision-maker reveals a deeper hesitation about its role in professional judgment. While they may enjoy experimenting with these tools, this limited use signals ongoing concerns about trust. As Burrell (2016) and Bathaee (2018) emphasize, explainability is crucial in shaping how professionals interact with AI. The unwillingness to delegate decision-making to AI reflects a broader unease with tools that lack transparency and accountability (Lehner et al., 2022). As Dennis (2024) points out, auditors' commitment to professional scepticism and ethical responsibility reinforces the need for human oversight—something clearly maintained by the participants in this study.

Participants further detailed how AI tools were particularly useful in locating legal frameworks or accounting standards. This demonstrates AI's strength in improving the accessibility of domain-specific knowledge, as noted by Issa et al. (2016). One participant explained:

"We also use AI to help find relevant legal provisions. If I ask a question, I get the answer immediately and can read further about what applies there. Most of the time, you have a general idea of what is legal or not, but it's difficult to remember exactly where things are stated in the law, and that's where generative AI is very useful."

Another participant echoed this efficiency-oriented use:

"I use it sometimes to quickly get answers to questions, like which accounting principle is applied in a specific case."

In terms of core audit tasks, participants highlighted that AI is primarily used to streamline consistency checks across financial documents—such as verifying that figures in the income statement match those in the notes. These tasks, described as time-consuming and repetitive, are now increasingly automated. One participant noted:

"For example, identifying if a '1' matches a '1' when comparing two figures—that sort of work can be minimized. And that allows us to focus more on qualitative aspects of our job."

This shift was especially valued during the execution phase of the audit:

"So, I'd say AI will be most helpful in the execution phase of the audit."

These examples reflect what Bible (2023) identifies as AI's ability to manage rule-based procedures, freeing auditors to concentrate on more complex, judgment-intensive areas. As Alles (2015) and Dowling & Leech (2014) note, this automation reduces cognitive strain and creates room for higher-value activities like risk analysis. In this way, participants expressed a form of relief comfort (Kolcaba, 2001), as automation alleviates routine burdens and supports more meaningful audit engagement.

However, this acceptance of AI for administrative efficiency stands in contrast to its more limited role in analytical tasks such as risk assessment or fraud detection—areas central to the

auditor's evaluative function. While research highlights AI's potential in advanced analytics (Anica-Popa et al., 2024; Issa et al., 2016), the study suggests that auditors remain cautious, reserving these responsibilities for human judgment. This gap reflects an ongoing tension between AI's technical promise and the levels of trust and comfort required for its deeper integration.

This contrast also brings out a contradiction: although auditors express comfort and even enjoyment when using AI for routine tasks, they simultaneously restrict its role to non-decisive areas. As Carrington and Catasús (2007) argue, auditors' sense of comfort is influenced by their ability to trust both the process and their accountability within it. The findings suggest that this comfort is currently limited to tasks where auditors retain control and oversight, indicating a boundary between AI as a tool and AI as a decision-maker.

The cautious use of AI was not limited to auditors; participants also described a similar restraint among clients. Generative AI was reportedly used behind the scenes, but had not yet reshaped clients' preparatory work. As one participant noted:

"They [clients] haven't really been heavily influenced by AI yet. AI might've helped a bit in the background—for example, allowing companies to look up information—but not in the preparation phase directly."

Another added:

"They've [clients] maybe been to a few training sessions, but many are still in the early stage."

This pattern reflects a shared hesitance across both auditors and clients, indicating that AI adoption is not just constrained by technological limitations, but also by cultural and professional norms. As Munoko et al. (2020) suggest, the auditing profession has historically been resistant to rapid technological change, often favouring gradual integration over disruptive shifts. Additionally, the divergence in AI tools across firms—where larger firms leverage advanced internal platforms while smaller ones rely on public tools—raises concerns about inequality in technological access, which may exacerbate existing disparities in audit quality (Zavodna et al., 2024).

Participants emphasized that the most successful implementations occurred when auditors had access to education and opportunities to experiment with AI tools, giving them space to develop their skills. This hands-on learning restored what Kolcaba (2003) calls psychospiritual comfort—confidence, clarity, and control in professional roles. As Kelly and Larres (2025) argue, comfort grows with competence. This was echoed across several interviews: auditors who had time to learn and reflect expressed stronger trust in their ability to work alongside AI.

At the same time, concerns around the quality of AI systems were also prevalent—especially regarding how the systems were trained. Some participants worried about blind spots or biases baked into the training data, especially if those datasets reflected outdated or flawed historical practices (Binns, 2018; Dablain et al., 2024). As one participant explained:

"AI can be really good at spotting patterns, but we're not always sure if it's trained on everything it needs to be trained on to catch all potential problems."

While this can enhance accuracy and relevance, it also carries risks. As Binns (2018) notes, training on historical data may inadvertently reproduce biases, particularly if those data reflect outdated standards, systemic inefficiencies, or unbalanced decision-making. Dablain et al. (2024) similarly highlight how skewed or incomplete datasets can generate unreliable outputs, complicating auditor's ability to trust results. This issue becomes even more pressing in high-stakes audit setting (Rahwan et al., 2019), where a lack of transparency can severely undermine cognitive comfort and evaluative confidence.

This underscores a central tension: while AI offers speed and broad applicability, its opaque decision logic is not always transparent. Without clarity on how AI arrives at its outputs, auditors face challenges in verifying outcomes, maintaining professional scepticism and audit quality. These limitations further reinforce the need for human review and ethical safeguards to ensure AI outputs remain aligned with current professional values and regulatory expectations (Dennis, 2024; Rahwan et al., 2019).

This challenge was even evident in the accounting profession, were transparency and traceability are central to audit quality (Goertzel, 2014). Without a clear understanding of how AI systems operate, auditors may struggle to judge the reliability of the outputs. As one participant explained:

"We don't always know to what extent AI is used in the accounting process. Since we don't see the whole process behind the scenes, it's hard to determine whether AI has had a noticeable impact on quality."

This relates directly to the black-box problem described by Bathaee (2018) and Lukyanenko et al. (2022), where lack of transparency undermines trust and weakens professional scepticism. As Mayer et al. (1995) note, trust depends on perceived ability, benevolence, and integrity—qualities that are difficult to assign to opaque systems. The need for interpretability thus becomes central —not only to uphold professional scepticism, but also to sustain the auditor's ability to engage critically and confidently with AI-generated information.

Despite these concerns, participants also shared compelling examples of how AI supports audit quality. One commonly mentioned strength was AI's capacity to process large data volumes and flag inconsistencies that humans might miss due to fatigue. As one participant explained:

"The same goes when we look for potential fraud. Often, it's about going through enormous amounts of data and spotting discrepancies. We humans can easily lose focus after a long time, but AI doesn't do that."

This mirrors insights from Issa et al. (2016), who argue that AI systems can support auditors by identifying anomalies across large volumes of transactions—tasks that are impractical for manual review.

While participants generally agreed that AI can improve the precision of audits by revealing issues that might otherwise go unnoticed, they also emphasized that this does not necessarily translate to faster audits. As one participant noted:

"Also, with improved audit quality, we may start uncovering more issues. The audits become sharper and more precise, but that doesn't always mean they'll be faster."

This statement reflects a central contradiction: efficiency gains may unexpectedly increase workload, as more anomalies require follow-up. Auditors' awareness of this tension also touches on strategic discomfort, where the tool's output complicates rather than supports task

flow. This supports findings by Fedyk et al. (2022), who argue that AI enhances performance but demands more thorough auditor involvement.

In light of these dynamics, participants consistently stressed the continued importance of human oversight. While AI can process data and flag anomalies, final judgments must remain with auditors. As one participant stated:

"We use AI as a support to get information quickly, but what we produce has to be our own work. We have to understand and stand behind what we deliver."

This aligns with Comfort Theory's concept of transcendence (Kolcaba, 2003), which highlights how individuals perform at higher levels when supported by technology. Auditors' emphasis on maintaining control over AI-generated outputs also reflects concerns raised by Emett et al. (2023) and Cao et al. (2022), who warn that over-reliance on automation may weaken professional scepticism.

Similarly, participants underlined that risk assessments—despite being enhanced by AI—must remain anchored in human judgment. While AI can flag anomalies, it is auditors who must contextualize them and decide their relevance. As one auditor clarified:

"It's not that AI independently does the entire analysis or draws conclusions for us. AI is more of a tool along the way, not a replacement for our work."

This statement underscores what Siau and Wang (2018) refer to as task augmentation, where AI supports rather than supplants human labour. The need to contextualize outputs is particularly important in auditing, a profession grounded in professional scepticism and governed by accountability (Francis, 2011).

In particular, participants noted that AI is ineffective in high-risk audits involving complex financial structures, regulatory ambiguities, or ethical dilemmas—areas where human interpretive capacity is indispensable. This resonates with Appelbaum et al. (2017), who argue that while AI can improve efficiency, it cannot replicate the nuanced reasoning required in judgment-heavy contexts. As one participant emphasized:

” For small audit tasks with low risk, I could consider using AI, but when the risks are higher, it’s harder to trust it.”

Another participant noted:

“There will still be a need for human judgment, especially in complex situations.”

Importantly, AI’s integration has also enabled a shift in auditors’ focus toward strategic and human-centred tasks, such as client communication and judgment-based analysis—roles that demand both expertise and interpersonal insight. This shift supports Sutton et al. (2016), who note that AI implementation is often more successful when it frees professionals to focus on higher-order thinking. One participant reflected:

“Many tasks like reviewing customer and supplier accounts are automated, which frees up a lot of time and makes audits more secure.”

Another participant added:

“… as [AI] gives more time for things that only humans can do.”

Yet this reallocation of attention also introduces new institutional contradictions. For instance, when clients use AI to generate management reports, auditors must evaluate not only the content but the integrity of the AI processes behind it. This added complexity reinforces the argument by Munoko et al. (2020) that the implementation of AI reshapes assurance work, not just in terms of efficiency but also in ethical responsibility and assurance depth, as one participant explained:

“We’ve heard some examples, such as that some clients have used AI to write their management reports. That can be a challenge for us auditors, as it may require additional review measures.”

In sum, while institutional pressures (DiMaggio & Powell, 1983; Meyer & Rowan, 1977) encourage generative AI adoption, its integration remains bounded by trust, comfort, and the auditor’s ethical role. The profession is not facing replacement but redefinition—a transition that demands both technological fluency and human judgment. As the findings show, auditors

are not resisting generative AI—they are actively negotiating its role, ensuring it complements rather than compromises the core values of auditing.

4.2 Trust, Uncertainty, and the Limits of Technological Comfort

In the interviews, auditors shared their perceptions of generative AI, which emerged as a prominent theme during the data analysis. Participants described varying levels of trust and comfort around generative AI systems, as well as the factors influencing these views. They also reflected on the role of professional scepticism and its continued importance in work. These insights highlight how auditors evaluate the trustworthiness of generative AI and how they apply their existing professional knowledge when engaging with new technologies.

Building on these perceptions, auditors consistently described AI as a practical tool designed to enhance their work rather than replace human judgment. This perception was rooted in AI's ability to improve efficiency, particularly through automating repetitive tasks and enabling rapid access to information. Participants welcomed these functions, especially within a profession often marked by long hours and high demands. As one participant noted:

"It's an industry where many people work far too many hours all year round, and in that case, AI might be a lifesaver for many auditors."

This perspective reflects how auditors tend to adopt AI when it serves to reduce administrative burden and streamline tasks, reinforcing earlier findings by Appelbaum et al. (2017) that technology is most readily accepted when it supports core professional goals without disrupting autonomy. However, this practical framing also reflects deeper institutional dynamics. As DiMaggio and Powell (1983) suggest, organizations often adopt technologies not only for their utility but to align with professional norms and maintain legitimacy. In this sense, auditors' acceptance of AI may be shaped as much by external expectations as by internal needs.

Despite this generally positive outlook, participants drew a clear line between traditional automation and more advanced forms of AI. Automation was viewed as deterministic and rule-based, while AI was described as increasingly generative—capable of suggesting solutions and producing content. As one participant explained:

"Automation is about predefined logic—no conclusions, just direct connections, very binary: ones and zeros. AI is more advanced—it can make suggestions or generate content. Much of what we use today is automation, but we're starting to see elements of AI."

This evolving perception suggests that AI is beginning to be seen not just as a tool but as a potential contributor to decision-making (Haenlein & Kaplan, 2019). However, with this shift came a growing unease around accountability. Some auditors described difficulties in identifying whether inconsistencies in reports were due to human error or AI-generated outputs. As one participant observed:

"We definitely come across errors in financial reports, but I don't know if they are due to AI or human mistakes."

Others pointed to opacity in AI's development and training data, raising concerns about potential gaps in the AI training data and the presence of biases (Dablain et al., 2024). As one participant pointed:

"There's also some uncertainty about what AI has been trained on and whether it could have identified loopholes in our review process."

This ambiguity points to what Bathaee (2018) and Doshi-Velez & Kim (2017) describe as the black-box problem of AI—when the reasoning behind outputs is inaccessible, making it difficult to verify results or assign responsibility. In auditing, where traceability and interpretability are essential, this lack of transparency creates discomfort and raises doubts about control, auditability, and assurance (Burrell, 2016).

In response, professional scepticism becomes a critical safeguard. As a cornerstone of auditing (Al-Qatamin & Salleh, 2020), it requires auditors to maintain a questioning mindset, to scrutinize data rather than accept it at face value (Nelson, 2009; Parasuraman & Manzey, 2010). Yet, while firms feel pressured to adopt AI for legitimacy (DiMaggio & Powell, 1983), auditors are often left without the tools or transparency needed to verify these systems. This reveals a deeper institutional contradiction: while coercive and mimetic pressures encourage AI adoption, the actual integration may exceed auditors' cognitive and procedural readiness

(Oliver, 1991). As Commerford et al. (2024) note, this has shifted scepticism from merely evaluating data to critically assessing systems producing it.

This lack of explainability creates a form of cognitive discomfort—auditors struggle to reason through outputs they cannot fully understand, weakening their analytical control and limiting confidence. In high-stakes contexts like auditing, explainability is not optional—it is a prerequisite for sound professional judgment (Rahwan et al., 2019). This was made clear by participants who emphasized the need for verification and traceability. As one participant shared:

"AI sometimes uses references, and you can also verify what is being said by reading the sources as well. It's important to be able to check the information yourself."

Another added:

"If AI could refer to, for example, FAR or other relevant sources, it would be much better."

These reflections resonate with Dirks and Ferrin's (2002) assertion that trust in systems is built through clarity and justifiability. Verifiability thus acts as a proxy for competence and integrity, which are central to Mayer et al.'s (1995) trust framework. When outputs could be understood and linked to authoritative standards, auditors reported greater confidence in their use. This process also contributed to what can be described as cognitive trust: the belief that not only is the output correct, but the reasoning behind it is coherent and accessible.

Building on this foundation, auditors described how AI's growing presence has required them to extend their professional scepticism beyond traditional evidence assessment (Al-Qatamin & Salleh, 2020). While they acknowledged AI's usefulness, they were unanimous in stating that it did not absolve them of the responsibility to critically evaluate audit evidence. As one participant made clear:

"In our work, it's us who must draw the conclusions. The audit is about our judgment—not the client's, not AI's, and not any external party's. It's our professional opinion that matters."

Rather than undermining scepticism, AI appeared to reorient it. (Brougham & Haar, 2018) argue that AI reshapes rather than eliminates the need for judgment, reinforcing auditors'

responsibility to ensure that outcomes are not taken at face value (Appelbaum et al., 2017). Adeoye et al. (2023) echo this view, highlighting the importance of critical scrutiny even when results are AI-generated.

This attitude translated into concrete practices that fostered a sense of relational comfort. Several participants emphasized the importance of layered review processes. As one auditor stated:

"Generally, I trust AI, but in our industry, it's very important to always have a review process. Whether it's a human or AI that has produced the material, it always goes through multiple review steps."

Another participant echoed this view:

"I think it's part of my job to be sceptical of the information, whether it's AI-generated or created by a human."

This form of scepticism was applied the same way to all sources, whether the information was produced by a human or a machine. This reinforces Kolcaba's (2003) notion of psychospiritual comfort, where confidence and clarity are deeply connected to a sense of professional control. Yet, the opacity of many AI tools often hindered this process. Without insight into how AI arrived at its conclusions, auditors described a form of cognitive discomfort that limited their ability to verify outputs. Auditors felt more at ease when AI-generated outputs could be logically understood and aligned with professional expectations. As one participant put it:

"It would also be helpful if AI explained why it provides a certain answer and how different choices affect the results. That would make me feel more confident in trusting the system."

While scepticism provided a protective stance, trust in AI was more contingent. Participants described trust not as something given, but as something built through familiarity, quality control, and institutional endorsement. As one participant put it:

"Trust comes from quality assurance. If the reports are generated through AI tools that are thoroughly quality-checked, then they can be just as good—if not better—than manual ones."

This perspective reflects Mayer et al.'s (1995) trust framework, in which trust arises from perceptions of ability, integrity, and benevolence. Auditors appeared to assess AI tools through the same lens, focusing on the system's reliability, ethical application and alignment with audit objectives. This reflects a broader emphasis on verification, with trust being contingent on confirming the reliability of both internal and client-provided AI systems (Lukyanenko et al., 2022). Trust also depended heavily on context. Internal AI systems embedded within the firm's routines and controls were generally accepted, while AI tools used independently by clients raised scepticism (Siau & Wang, 2018). As one participant noted:

"As long as [the clients] can trust their data, we can trust it too."

Another added:

"First, we want to know what kind of AI tools the client has used. Can we trust those tools? If not, that's a concern, and we'd need to investigate further."

These insights reveal that trust in AI is shaped not only by technical performance but by institutional embedding—whether auditors perceive AI as part of a controlled and auditable process. This aligns with Rahwan et al. (2019), who argue that AI systems are more likely to be trusted when visibly governed by human oversight and professional standards. Importantly, trust was often mediated through human expertise.

Alongside trust, comfort with AI was not solely dependent on system performance—it was relational and contextual. Many participants preferred turning to colleagues over relying on AI in ambiguous situations. As one auditor explained:

"It makes me prefer to turn to a colleague rather than AI, because a colleague can give a more in-depth explanation."

This reflects how comfort is fundamentally relational. As Laux (2024) observes, comfort is not just about what a system can do—it's about how that system is supported by human interactions, norms, and shared understanding. These dynamics were especially visible across generational lines. As one participant noted:

"The older people at the firm were quite sceptical and uncertain about how to use AI. They weren't really open to it. The younger ones were more interested and saw the potential of what AI could do."

This generational divide aligns with findings by Siau and Wang (2018) and Hauk et al. (2018), who show that comfort with technology is closely linked to exposure and digital fluency, creating a cognitive familiarity with technology. Psychospiritual and sociocultural comfort (Kolcaba, 2003) were highest when auditors had both the technical ability and the social environment to explore AI's functions with confidence. In this context, two interrelated dimensions of comfort became particularly significant: developmental comfort, enabled through learning, training, and exposure to new systems; and cognitive comfort, rooted in auditors' ability to reason through AI-generated information with clarity. These dimensions were not experienced in isolation. Rather, they worked together to shape how comfortable auditors felt navigating AI-enabled environments—especially for younger auditors, who more frequently described confidence across the two dimensions. Nevertheless, there was a shared belief across generations that AI enhances efficiency by relieving professionals of tedious and repetitive tasks—linking back to physical comfort, as defined by Kolcaba (2003), and reinforcing trust in AI's ability to support more meaningful audit work.

Physical comfort also emerged in relation to task efficiency. Many auditors appreciated how AI could reduce repetitive work, allowing them to focus on more analytical tasks. One participant summarized this well:

"I would say most [colleagues] are positive because AI allows us to work faster and easier. That's the general attitude."

This reflects what Kolcaba (2001) refers to as transcendence—a type of comfort linked to enhanced performance—and aligns with Nickell et al. (2023), who found that automation increases job satisfaction by freeing cognitive resources for higher-value work.

However, this functional gain also introduced a form of cognitive discomfort, driven by limited developmental opportunities. Some participants described the pace of technological change as overwhelming. As one auditor put it:

"It's a challenge with so much new stuff—it can feel uncomfortable working with so many new tasks and technologies."

Francis (2011) observed that audit innovation often increases uncertainty, especially when it outpaces the capacity for training and adaptation. Even when tools are efficient, rapid change can undermine the sense of professional stability. This concern echoes broader institutional insights: adoption without meaningful integration creates shallow change and can destabilize assurance norms (Lehner et al., 2022; Mardijuwono and Subianto, 2018).

Still, comfort was often restored when AI was implemented within clear and stable frameworks. Structured systems that preserved human oversight and aligned with established procedures gave auditors a sense of environmental control. As one participant reflected:

"Yes, within the framework of how we use AI today, I feel secure."

This supports Kolcaba's notion of environmental comfort, where predictability and alignment with professional norms foster a sense of safety and control (2003). Comfort was not simply a reaction to AI itself—it was a reflection of how well AI was embedded in trusted systems, supported by transparent processes, and surrounded by human expertise. Additionally, participants described a form of comfort rooted in their trust in the audit team's ability to identify and correct errors—acting as a critical safeguard. The degree of comfort or discomfort auditors experienced was therefore influenced not only by the nature of AI but also by their ability to adapt, exert control, and incorporate these technologies into their workflows in ways that aligned with their professional values and expectations (Dowling & Leech, 2014). These findings underscore the importance of thoughtful integration: when new technologies are introduced with clear explanations and appropriate training, they foster both developmental and strategic comfort by increasing auditors' understanding and control over their use.

These findings suggest that generative AI does not inherently generate comfort. Instead, comfort is a conditional outcome, shaped by explainability, professional norms, peer support, and institutional design. When these elements are present, auditors are more likely to feel confident in verifying and assessing AI-generated financial data. In their absence, uncertainty —and with it, discomfort—tend to prevail. This indicates that the relationship between generative AI and audit quality is not purely technological but fundamentally relational.

Comfort, and the trust that supports it, must be actively constructed for generative AI to become a credible part of the assurance process.

4.3 The Tension of Job Stability in an Automated Profession

The development of generative AI is not only changing how audits are conducted, but also how auditors perceive the future of their profession. Participants described a field shaped by the themes of institutional pressures, evolving skill demands, and growing uncertainty around job roles. The future of profession emerged as an aggregated dimension, reflecting how auditors view the future of their profession and how it will be affected by the implementation of generative AI. This includes how and why the implementation of generative AI is happening, along with the effect that has on the auditors' jobs and the skills they have to develop.

As previously mentioned, institutional pressures are a big part of why audit firms are implementing generative AI. A consistent narrative across interviews was the drive to remain competitive in the face of rapid technological shifts. AI was largely framed as a tool for efficiency and strategic advantage. Larger firms, in particular, were seen as front-runners in this transformation. As one participant noted:

"Larger firms are investing heavily in AI because it gives them a competitive edge. Smaller firms might have a harder time keeping up, which could increase the gap between large and small auditing firms."

This perception reveals the mimetic forces at play, especially among smaller firms which felt compelled to emulate larger competitors already integrating AI (DiMaggio & Powell, 1983). This dynamic reinforces existing power hierarchies within the industry: larger firms act as institutional leaders, setting technological and professional benchmarks (Munoko et al., 2020). For smaller firms, imitation becomes a survival strategy, not necessarily an innovation choice (Kend & Nguyen, 2022). However, this pressure has a dual effect: while it encourages innovation, it can also lead to discomfort—especially among auditors in resource-constrained environments—who may feel lacking the necessary tools to meet rising expectations. As a result, trust in one's professional capability and firm's competitiveness becomes contingent on the capacity to keep progress.

Still, the perceived threat of AI adoption varied. As one participant noted:

"My first thought is that it doesn't make a huge difference—at least as long as both use AI to the same extent. But if there's a gap in usage, then it could make an impact. That said, large and small firms often target different clients. So I don't see it as a major issue."

This statement illustrates that competitive dynamics were not viewed monolithically. While some participants saw AI as widening the gap between large and small firms, others emphasized client segmentation as a buffer (Yang et al., 2024). This suggests a reframing of competition, viewing it less as competition and more as strategic differentiated within market segments. In this light, the pressure to imitate may be overstated. Rather than being driven solely by institutional conformity, firms may adopt technologies selectively, aligning with their strategic priorities and client needs (Battilana et al., 2009).

Such interpretation challenges deterministic views of Institutional Theory by emphasizing organizational agency (Oliver, 1991). While some auditors feel destabilized by the pace of technological change, others maintain a sense of comfort through role clarity and market positioning. These diverging responses reveal that perceptions of audit quality and trust in AI integration are shaped not only by external pressures, but also by whether AI is seen as a tool for strategic enhancement or as a threat to established practices.

Evidence also pointed to an evolving market structure. As one participant observed:

"A company has started releasing the smaller clients they have, which means they are focusing more on their bigger clients. This leads to the smaller clients eventually coming to us, the smaller firms."

This redistribution of clients presents a tension: while it offers growth opportunities for smaller firms, it also introduces new pressures. These firms must now deliver high-quality audits without the technological infrastructure or financial capacity of larger peers (Zavodna et., 2024). As one participant noted:

"Naturally, larger organizations have more financial muscle to implement these tools. That makes a difference."

The uneven access to AI tools—driven by disparities in financial resources—was a recurring concern. This restructuring reflects a core insight of Institutional Theory: as larger firms set the pace of innovation, structural inequalities are not only sustained but potentially deepened through isomorphic pressures (Powell & DiMaggio, 1991). Smaller firms gain access to new markets but must keep up with rising expectations, often without the necessary means (Munoko et al., 2020). As a result, comfort with AI and trust in its contribution to audit quality becomes unevenly distributed, favouring auditors operating in better-resourced environments. This emerged in relation professional development, as it creates a knowledge gap for auditors. As one participant noted:

"When AI is there, it does part of the job for you, which means you don't learn the job that AI is doing for you."

This concern reflects a deeper institutional tension between technological efficiency and professional expertise (Guénin-Paracini et al., 2015). While AI may streamline processes, it risks eroding auditors' foundational knowledge, ultimately affecting their ability to exercise judgment—central to audit quality and professional identity. This tension highlights an essential aspect of institutional isomorphism: the balance between embracing technological change and maintaining the professional autonomy and judgment that have long been central to the auditing profession (DiMaggio & Powell, 1983). The development of a professional identity that is deeply intertwined with both technological competence and critical judgment is vital for sustaining trust in the audit process.

The adoption of AI is also reshaping roles and responsibilities, especially in larger firms. As one participant observed:

"In large firms, there's a shift towards more advisory roles and the social aspect. You meet with clients more."

Another participant furthered this notion by stating:

"It's expected that a certain percentage of tasks will disappear, and new hires will have different types of tasks than before."

These changes suggest that AI may be redefining the nature of auditing work. By automating routine and repetitive tasks, AI frees up auditors to engage more deeply with clients and provide strategic insights—a trend aligned with the broader move toward market-oriented professionalism (Anderson-Gough et al., 2000). This shift also places greater emphasis on the human dimensions of auditing, including communication, interpretation, and ethical reasoning. It also shows that the human role in auditing would always be necessary. This was unanimous in the interviews, and the participants expressed that AI would not be able to completely take their job. Thus, the participants did not view AI as a threat to their job. Participants further reinforced this sense of stability by noting that no job losses had occurred due to AI:

"I don't think anyone has lost their job due to AI so far."

This belief fostered a form of environmental comfort (Kolcaba, 2003), where stability and predictability in professional roles are preserved despite technological advancement. However, this reassurance was not without contradictions. While participants did not fear for their own jobs, they expressed unease about the automation of entry-level tasks traditionally performed by juniors. As one participant noted:

"... but audit assistants may be replaced by AI since many tasks can be handled automatically."

This duality reflects the tension embedded in AI's implementation. While the technology improves efficiency and audit quality by reducing human error (Appelbaum et al., 2017), it also risks displacing the very tasks that help junior staff develop the skills necessary for long-term growth (Ernst et al., 2019). As one participant explained:

"The tricky part is that it will likely be the demand for junior auditors that decreases, not senior ones. But if there are fewer junior auditors, it will be difficult to develop senior auditors in the future."

This concern echoes Malik et al. (2021), who argue that while AI may streamline certain processes, it can simultaneously hinder professional development by displacing tasks that facilitate learning resulting in less competence and confidence. Similarly, Bhargava et al. (2021) suggest that fears of job displacement diminish trust in AI systems, indicating that trust

in AI is heavily influenced not only by its competence but also by auditors' sense of security within their profession. The result is a form of strategic and developmental discomfort—auditors feel uncertain not about AI's immediate utility, but about whether they will have the developmental space to grow within the profession. In this sense, a robust system of continuous education and training becomes crucial to creating developmental comfort. This was mirrored in the interview, one participant explained:

"But when things change, you have to keep up with developments to stay attractive on the job market. It's always important to adapt and learn new tools."

The erosion of junior roles also threatens the continuity of expertise in audit firms. Experienced auditors rely on structured pathways for skill-building, and when these are disrupted, the perceived quality of audits is also at risk. As one participant emphasized:

"At the same time, a challenge arises: if AI takes over the simpler tasks that new employees traditionally do, it might be difficult to build a solid foundation for learning. Normally, a new hire at an audit firm starts with basic tasks and gain experience."

This indicates that the old skills are still necessary, as they provide experience that is necessary for an auditor to apply their professional scepticism. Thus, without this experience, their competence may be lacking, even if they have developed a new set of skills that are necessary when working alongside AI. As AI-driven tools become more integrated into audit processes, auditors must balance the comfort of traditional methods with the necessity of adapting to new technology (Alles, 2015; Novizhilova et al., 2024). This shift requires technical proficiency, including an understanding of AI algorithms and the ability to assess and ensure the accuracy of AI outputs (Gerlich, 2023). The evolving skill set reflects broader trends across industries, where digital literacy and advanced technical capabilities are increasingly in demand. Auditors who can effectively integrate AI tools into their workflows will be better positioned to add value in areas such as data analysis and fraud detection (Appelbaum et al., 2017). As one participant noted:

"*For job security, it's about adapting, acquiring new skills, and trying to advance before AI takes over the simpler tasks."*

This reflects a broader pattern across professions, where individuals increasingly find themselves "racing with the machines" to stay ahead of technological displacement (Bruun & Duka, 2018). Additionally, the way organizations manage AI integration also shaped perceptions of job security. Several participants emphasized that the impact of AI was not just technological, but strategic. One participant stated:

"With a good client flow, I don't think it will impact the employees too hard, it will just make their jobs easier. But if a firm doesn't aim to take in more clients, then I think it could have a negative impact on employees, of course."

This view is in line with Kokina et al. (2025), who suggest that the way firms choose to utilize AI—whether by expanding client portfolios or redistributing saved time into higher-value tasks—has a direct impact on employees' sense of security. Participants noted that AI itself was not the source of concern, but rather how organizations respond to the efficiency it creates. This aligns with Siau and Wang's (2018) argument that trust is not fixed but shaped by the surrounding context and ongoing strategic decisions. Thus, the strategic comfort comes from the alignment with the company's goals. One participant even expressed:

"I think there are different factors that can affect the outcome [of AI implementation]. It's more about what goals the firms have."

The concept of institutional logics helps explain these strategic decisions. In the auditing profession, firms must navigate both professional and market logics. Professional logic emphasizes ethical standards, regulatory compliance, and scepticism in financial reporting, while market logic pushes firms to prioritize profitability, client retention, and service expansion (Anderson-Gough et al., 2000). The tension between these competing logics is visible in how firms adopt AI: larger firms may be more equipped to align AI initiatives with both professional and market goals, giving them a competitive edge, as seen in participants' comments about AI's potential to expand client bases. This reflects how leaders interpret and balance these institutional pressures, demonstrating the role of human agency in shaping organizational strategies (Battilana et al., 2009; Thornton & Ocasio, 1999). When firms use AI to pursue new growth opportunities, such as expanding their client base or moving into areas like sustainability audits, auditors' sense of security and purpose is strengthened. In this way,

trust in AI's role is deeply tied to the firm's broader strategy. This was also present in the interviews, as one participant highlighted:

"One solution could be to focus more on sustainability auditing. The demand for sustainability auditors is growing quickly, and that's an area where AI probably can't replace human expertise to the same extent."

This also shows that auditors view sustainability auditing as a possible future career-advancement. This can partly be because sustainability auditing relies on subjective and qualitative analyses which requires a high degree of professional judgement (Camilleri, 2024). Thus, sustainability audits necessitate a nuanced understanding of non-financial factors, such as environmental impact, social responsibility, and government practices, which makes these tasks harder to fully automate (Minkkinen et al., 2024). Auditors expressed more comfort and trust when their human expertise remains irreplaceable, reinforcing Kolcaba's (2003) notion that comfort is enhanced when one feels essential. In this context, sustainability audits offer a counterbalance to the displacement of traditional audits and thus offer firms a new market to invest into for the sake of their employees and the technological advancement that is taking place.

These findings also mirror Ehlers (2021), who suggests that perceptions of benevolence and long-term investment by the organization influence employees' trust in technological change. When AI's implementation aligns with employee development and organizational growth, it strengthens both strategic comfort and institutional trust. Conversely, when AI adoption is perceived as prioritizing cost-cutting over human development, it introduces discomfort, scepticism, and questions of fairness. This reinforced the idea that auditors' comfort depends not only on their trust in the technology, but also in the competence of their colleagues and employers. When foundational skills erode due to automation, this trust can erode—undermining their relational comfort and contributing to a decline in perceived audit quality. Thus, when auditors feel the system does not prioritize their job, their sense of security diminishes, increasing discomfort around AI technology.

Finally, the regulatory landscape emerged as both a current concern and a future enabler of AI integration. Participants pointed out that existing standards have yet to fully accommodate the

complexities introduced by AI, particularly in areas such as ethical guidance, risk assessment, and quality control. As one participant explained:

"I think both policy and regulation will need to adjust. Over time, standards will also start to treat AI-generated information differently, recognizing new risk factors. That's definitely part of the equation."

This highlights how evolving regulatory frameworks are central to resolving uncertainty in AI adoption. While firms are already experimenting with new tools, auditors remain constrained by outdated standards that have not caught up to technological developments (IAASB, 2018; Lehner et al., 2022). Coercive pressures thus serve a dual purpose: not only do they enforce compliance, but they also provide legitimacy and structure. As regulators adapt, they create clearer expectations and reduce ambiguity—critical for fostering comfort and rebuilding trust in AI-assisted audit processes. In this sense, regulation is not simply a constraint, but a mechanism that can both stabilize the profession and support its transformation (IAASB, 2014).

In sum, auditors' comfort and trust regarding job security are not simply shaped by whether AI eliminates jobs, but by how it reshapes professional identity, growth opportunities, and organizational responses—aspects that can also affect their sense of purpose and relevance (Selenko et al., 2022). When AI supports rather than supplants auditors—complementing rather than replacing their expertise, both comfort and trust are strengthened. However, if AI's integration erodes traditional development pathways or lacks transparency, it risks triggering discomfort and mistrust (Siau & Wang, 2018). The future of job security in auditing will depend not just on technological innovation, but on how effectively firms balance automation with long-term professional sustainability.

5 Conclusion

The fifth chapter aims to conclude the study, wrapping it up. It will reflect the theoretical and empirical findings and discuss the relevant societal implications of the study. Limitations and future research will be closing the study.

5.1 Conclusion

This study sets out to explore how generative AI influences auditors' comfort in verifying and assessing AI-generated financial data. By integrating Comfort Theory (Kolcaba, 2003), Trust Theory (Mayer et al., 1995), and Institutional Theory (DiMaggio & Powell, 1983; Oliver, 1991), and analysing qualitative insights from Swedish auditors, the research provides a nuanced understanding of how auditors experience the digital transformation of their profession.

The findings suggest that generative AI integration is not a straightforward technical process, but a socially embedded negotiation shaped by institutional pressures, organizational strategy, and professional expertise (Jeong & Kim, 2019; Siau & Wang, 2018). While generative AI is seen as a valuable tool for efficiency—especially in automating routine tasks (Appelbaum et al., 2017; Issa et al., 2016)—its use in judgment-heavy tasks remains limited. This is due to auditors' discomfort with generative AI's opaque logic (Bathaee, 2018; Burrell, 2016), and the continued necessity of human oversight in risk assessments and client communication (Cao et al., 2022; Francis, 2011).

Trust in generative AI was found to be contingent on transparency, system integration, and whether auditors felt their own judgment remained central to the audit process (Mayer et al., 1995; Rahwan et al., 2019). Institutional factors—especially resource disparities between large and small firms—also played a critical role in shaping comfort and perceived audit quality (Munoko et al., 2020; Zavodna et al., 2024). Concerns about job displacement were more pronounced among junior auditors, as generative AI increasingly automated foundational tasks needed for skill development (Ernst et al., 2019; Malik et al., 2021).

Yet, the study also highlights pathways forward. Participants emphasized that with sufficient training, explainability, and structured integration (Nickel et al., 2023), generative AI can be seen as a complement rather than a competitor (Rahwan et al., 2019). Strategic use of generative AI to expand client offerings, such as in sustainability audits, provided new career pathways and reinforced professional relevance (Camilleri, 2024; Minkkinen et al., 2024). These findings suggest that the future of generative AI in auditing depends not only on technological innovation but on the institutional commitment to supporting professional growth and sustaining audit quality.

In conclusion, the study finds that generative AI does not inherently erode or improve audit quality—it reshapes the conditions under which comfort, trust, and professional judgment are developed. For AI to become a credible and integrated part of auditing practice, comfort and trust must be intentionally cultivated, not assumed. These insights provide a foundation for rethinking how we support professionals in technology-intensive fields and offer a revised model of comfort more suited to modern work environments.

5.2 Contributions

While Comfort Theory (Kolcaba 2003) is well established and widely applied in the nursing profession, its four dimensions have limited applicability across other professional contexts. Tech-driven industries, where many people work in systematic ways with computers, differ significantly from the healthcare environment (Carrington & Catasús, 2007). Consequently, the use of Comfort Theory within the auditing profession has remained scarce. Still, this does not reduce the importance of understanding the comfort of auditors and other professionals in tech-oriented fields. As this study applied Comfort Theory to the auditing context, it became clear that auditors' experiences of comfort did not fully align with the traditional dimensions developed for nursing.

According to Kolcaba (2003), the four dimensions of comfort are physical, psychospiritual, environmental, and sociocultural. These dimensions reflect the common challenges faced by nursing staff—whose work involves physical strain, exposure to changing environments, and emotional pressures. In such contexts, comfort is shaped by bodily fatigue, mental well-being, workplace conditions like lighting and noise, and social support systems. These dimensions are summarized below:

Dimension of comfort	Definition	Description
Physical	Bodily needs and physiological mechanisms	Relief from physical discomfort such as pain, fatigue or other bodily strains
Psychospiritual	Internal awareness of self	Emotional well-being, confidence, and a sense of purpose
Environmental	External surroundings and influences	Lighting, temperature and noise that affect ease and comfort
Sociocultural	Social belonging, shared norms	Feeling of belonging, social support and cultural acceptance

However, these dimensions did not translate neatly into the auditing context. As auditors primarily work in controlled office environments, they do not face the same physical or environmental discomforts (Bridger & Brasher, 2011). Lighting, noise, and posture-related concerns are usually minimal or easily managed. Psychospiritual comfort, however, was still relevant—particularly as auditors navigate complex demands, responsibility, and high-performance expectations (Carrington & Catasús, 2007). Sociocultural comfort also appeared in the form of collaboration and team dynamics. Still, these dimensions lacked depth in capturing what makes auditors feel comfortable in their work—especially in relation to technology, decision-making, and assurance quality.

Furthermore, when discussing comfort in auditing, it is more closely related to quality assurance than to physical strain (Carrington & Catasús, 2007). Through the data analysis in this study, new dimensions of comfort began to emerge. These dimensions reflect auditors' need for assurance and security when working alongside technology and in the face of uncertainty. The identified dimensions are cognitive, relational, developmental, and strategic. Cognitive comfort is derived from understanding technology and the logic behind it, often supported by familiarity with similar tools. Relational comfort arises from robust systems and procedures that auditors can rely on—systems that also distribute accountability, creating a sense of ease and reducing pressure. Developmental comfort stems from having the opportunity to learn new skills, explore tools, and grow within one's role. Strategic comfort, finally, is achieved when technology is

aligned with company goals and is clearly perceived as a competitive advantage. These new dimensions can be summarized as following:

Dimension of comfort	Definition	Description
Cognitive	Understanding and reasoning	The ability to comprehend, apply logic, and reasoning skills
Relational	Trust in colleagues and processes	Reliable processes, shared accountability, and confidence in colleagues' competence
Developmental	Ability to learn and progress	Opportunities for growth, skill development, and proper training
Strategic	Alignment with organizational goals	Organizational support, improvement security, competitiveness

These new dimensions align with Kolcaba's original types of comfort—ease, relief, and transcendence—but manifest differently in an office-based, tech-driven setting (Kolcaba, 2001). Auditors experience ease through understanding and familiarity, relief through dependable systems and supportive colleagues, and transcendence when they are empowered to grow and align their work with broader organizational strategies (Kolcaba, 2001). In this way, the core idea of comfort remains, but its expression shifts to fit the nature of contemporary audit work. The main contribution of this research is therefore the development of an adapted model of comfort that better reflects the realities of auditors working in environments shaped by technological change and professional accountability.

5.3 Implications

This study presents several key implications for the auditing profession, firms, AI developers, and policymakers.

For auditors, the integration of AI into auditing workflows calls for significant adaptation in their roles (Brougham & Haar, 2018). While AI tools can streamline routine tasks, auditors will

need to focus more on interpreting AI-generated insights, offering strategic advice, and exercising professional judgment (Almufadda & Almezeini, 2022). To effectively navigate this shift, auditors must develop new skills and enhance their technical knowledge. This means that training programs will be essential to ensure auditors feel confident using AI tools and are equipped to make the most of their capabilities.

For auditing firms, embracing AI offers opportunities to improve efficiency, reduce costs, and enhance service offerings (Issa et al., 2016). However, the implementation of generative AI should be managed thoughtfully. Firms should prioritize proper training and communication to ensure that auditors understand the role of AI in augmenting their work, rather than replacing it (Abdullah & Almaqtari, 2024; Venkatesh & Davis, 2000). This approach will help mitigate any resistance or concerns. Moreover, as AI takes on more routine tasks, firms should consider evolving their business models, shifting towards more value-added services like data analysis, risk management, and strategic advisory.

AI developers must focus on creating tools that are not only powerful but also user-friendly and transparent. For AI systems to be effective in auditing, they must be designed with auditors' needs in mind, offering clear explanations of AI-generated results and ensuring that auditors retain control over decision-making. Ethical considerations, including data privacy and avoiding algorithmic bias, are also crucial in developing trustworthy AI tools for the profession.

Finally, policymakers and regulators will play a vital role in ensuring that auditing standards are updated to accommodate AI tools. Regulations should ensure that AI-generated results meet high standards of transparency, accuracy, and accountability. Additionally, as AI may impact employment in the auditing field, policymakers should consider support measures for workers who may need to reskill or transition into new roles due to increased automation.

5.4 Limitations

One of the primary limitations of this study is the gap between the current state of generative AI adoption within auditing in Sweden and the level of integration that exists in other regions, particularly the US and similar countries. While the literature reviewed for this study highlighted significant advancements in AI technology in auditing practices (Anica-Popa et al., 2024; Bible, 2023; Kend & Nguyen, 2022), this research found that AI implementation in

Swedish auditing firms is not as advanced, with many auditors still in the early stages of adopting AI tools. This disparity between literature and practice may be a critical factor that influenced the findings, as auditors in Sweden are yet to develop sufficient practical experience with AI to make comprehensive evaluations of its potential and limitations. This was also evident in our data, as one participant noted:

"A lot is happening this year. I think the real effects will be seen in reports for fiscal year 2026—those financials will likely be more supported by AI-based audit processes."

Moreover, this study was conducted during a period when generative AI technology was still in the early stages of adoption within the auditing profession. As such, many auditors had limited exposure to or training in AI tools. Their perspectives may therefore have been shaped by uncertainty, and lack of confidence in emerging technologies, and a fear of the unknown (Cutter et al., 2009). The study also found that participants had mixed reactions to AI's potential in auditing— some expressed concerns about the implications of relying on AI, while others were apprehensive about its impact on their professional roles. This sense of uncertainty, common in the face of technological disruption, may have influenced their responses, as many had not yet had sufficient time to adapt or gain practical experience with AI.

Additionally, the limited scope of AI tools available in auditing at the time of the study may have influenced the findings, as only a narrow subset of AI capabilities was being tested and implemented. Auditors with minimal exposure to these early-stage AI tools might likely had limited insight into the broader potential of AI in auditing. Therefore, the findings of this study should be viewed with caution, as they reflect a specific point in time within the ongoing evolution of AI adoption in auditing.

Furthermore, a linguistic shift is emerging around the concept of AI. While artificial intelligence has existed for decades and continues to evolve (Sandewall, 2014), its earlier focus on efficiency and automation (Haenlein & Kaplan, 2019) did not attract as much public attention. Today, the rise of generative AI has brought AI into the public consciousness, creating a clearer distinction between different forms of AI. Many now equate "AI" specifically with generative AI, while automation-based systems are simply regarded as "technology". This distinction was also evident in our data, as one participant noted:

"We work a lot with automation rather than pure AI, as these are two different things."

The shift has implication for the current study. Auditors—generally not deeply embedded in technological discourse —appear to share the public's understanding of AI. Although this study focuses on generative AI, the distinction made by participants between AI and automation posed a challenge during the empirical analysis, as it may have influenced their perception of AI. Participants generally viewed automation positively, while expressing more critical attitudes toward AI. This suggests that they perceived some forms of AI as beneficial and other with scepticism, creating internal contradictions in their responses without necessarily being aware of it. Moreover, it was occasionally unclear whether participants were referring to generative AI or automation, which limited the interpretability of some parts of the data.

5.5 Future research

The most prominent future research emerging from this study is the need to further explore these new newly identified dimensions of comfort. These dimensions should be examined in future studies, particularly across various tech-driven industries. Such research could contribute to the development of a broader, more adaptable Comfort Theory, making it applicable to a wider range of professional contexts. Since these finding represent a potential new branch within Comfort Theory, additional empirical evidence is essential to validate and refine this emerging model. Therefore, further studies are necessary to build a foundation of empirical data and theoretical insight on how Comfort Theory applies within the auditing profession and other technology-oriented field.

One of the main limitations of this study is that the participating auditors had limited practical experience with generative AI, partly because AI technologies have not yet been fully developed or widely implemented across the auditing profession. As such, future research should revisit this topic in a few years, when AI tools are more advanced and better integrated into audit workflows. By that time, auditors may have accumulated more meaningful experiences, enabling them to reflect more critically on AI's impact and articulate how it has influenced their professional practices.

Lastly, this study suggests exploring the extent to which AI poses a real threat to auditors' job security. Many participants expressed concern that future generations of auditors may need to

navigate their careers differently due to increasing automation. This could form the basis for research on evolving career paths and shifting skill demands. In addition, several participants noted a belief that fewer auditors will be needed in the future. This raises important questions about recruitment patterns, and future studies could investigate whether hiring rates at audit firms are declining in response to greater AI adoption.

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7 Appendix

7.1 Appendix 1: Revised interview guide in English

1. **Background and Experience**

- Can you describe your role and responsibilities as an auditor?
- How many years have you worked in auditing?
- Can you tell me about your clients?
    - What type of clients do you usually work with?

2. **AI in Auditing**

- Can you explain how you use AI in your auditing/work process?
- In which areas of auditing do you see AI as most useful (e.g., risk identification, fraud detection, data analysis)?
- What changes have you observed in the auditing process due to AI integration?
    - Can you share specific examples?
    - Does AI/automation take over repetitive tasks?

3. **AI in Accounting**

- How has the growing presence of AI in accounting affected the way audits are conducted?
- In what ways has AI impacted the quality of financial reports, both positively and negatively?
- Have you encountered situations where AI-generated financial data contained errors? How were these identified and addressed?

4. **Comfort with Reviewing AI-Generated Data**

- How do you feel about conducting audits of financial data produced with the help of AI?
    - How do you feel about trusting AI-generated audit results?
- How has AI affected your ability to apply your expert judgment/professional opinions in auditing?
    - Can you describe a situation where AI-generated results conflicted with your professional judgment? How did you handle it?

- How do you view AI's role in improving the speed and efficiency of audits? Do you see any trade-offs or new challenges?

5. Skills Adaptation and Training

- What type of training have you received on AI in auditing, and how has it affected your work?
- What additional training or support would help you feel more confident in using AI in audits?
- How do you feel your skills need to adapt to keep up with the developments driven by AI?
    - Do you need new skills to feel relevant and useful?

6. Trust in AI-Generated Financial Data

- How would you compare your trust in AI-generated financial reports with traditional manual audits?
- What factors influence your trust (or lack of trust) in AI-generated data?
- Do you feel confident in what you do and how it is done?
- How clear are AI-generated results to you? Do you feel you can fully understand how AI arrived at its conclusions?
- How do you think AI can improve your work by providing more detailed explanations of the steps or logic behind audit conclusions?
- Can you describe an instance when AI results were difficult to verify due to a lack of explanation?

7. Institutional Pressures and Generative AI Adoption

- How do you think society's use of AI has influenced your implementation of AI?
- Do you think your company implements AI because it is beneficial for you or because of the standardization of AI?
- How do you view AI's role in future audit regulations and standards?
- How do you think AI adoption affects competition between large and small audit firms?
- How have your colleagues or clients reacted to the increasing use of AI? Have you encountered resistance?

8. Job Security and AI's Role in Auditing

- How do you view the profession's future in the presence of AI?
- How do you think AI is influencing career paths and job security for auditors today and in the future?
- What do you think about the challenges AI may pose for human auditors? And what do you think are the ways to handle these?

9. Closing Questions

- Is there anything else you would like to add about working with AI?
- Are there any feelings or experiences you think have not been expressed yet in this interview?
- Would you have time for an additional 10-minute interview later to address further questions that may arise as this study progresses?

7.2 Appendix 2: Original interview guide in English

1. Background and Experience

- Can you describe your role and responsibilities as an auditor?
- How long have you been working in auditing?
- What type of clients do you usually work with?
- Have you used AI-based tools in your audits? If yes, which ones?

2. AI in Auditing

2.1 Experience with AI Tools

- How often do you use AI-based tools in your audits?
- What types of generative AI tools or software have you encountered in your work?
- In which areas do you see AI being most useful in auditing (e.g., risk identification, fraud detection, data analysis)?
- Have you noticed any changes in the audit process due to AI? If yes, what are they?

3. Generative AI in Accounting

3.1 Experience in Reviewing AI-Generated Information

- When AI is used in accounting, how does the review of data produced by AI differ from traditional auditing?
- Have you noticed any differences in the quality of financial reports due to AI?
- Have you encountered errors in AI-generated financial reporting? How were they handled?
- What challenges has AI brought to the audit process, if any?

3.2 Comfort with Reviewing AI-Generated Data

- How do you feel about reviewing financial data produced with the help of AI?
- Do you trust financial reports where generative AI has been used? Why or why not?
- Has AI affected your confidence in your work?
    - Do you feel confident in what you do and how it is done?

4. Comfort with AI in Auditing

4.1 Perceived Impact on Work Processes

- Do you feel comfortable relying on AI-generated audit results? Why or why not?
- How has generative AI affected your ability to use your expertise and professional judgment in auditing?
- Do you think AI improves the speed and efficiency of auditing, or does it bring challenges that counteract any efficiency benefits?
- Have you experienced situations where AI made mistakes or misinterpretations? How did you handle it?

4.2 Adaptation of Skills and Training

- Have you received any formal training on how to use AI in auditing?
- What type of training or support would make you feel more confident in using AI in auditing?

5. Trust in AI-Generated Financial Data

5.1 Reliability and Accuracy

- How much do you trust AI-generated financial reports compared to traditional manual auditing?
- What factors influence your trust (or lack of trust) in AI-generated data?
- Have you experienced instances where AI's results did not align with your own judgment? How did you handle it?

5.2 Transparency and Explainability

- How clear do you find AI-generated audit results? Can you understand how AI arrived at its conclusions?
- Do you think AI should provide more detailed explanations of the steps or logic behind its conclusions? Why or why not?
- Have you encountered a situation where AI's results were difficult to verify due to a lack of explanation? How did you handle it?

6. Institutional Requirements and AI Usage

6.1 Regulatory and Industry Requirements

- Can you describe any requirements or expectations you experience from regulators, industry standards, or your employer regarding the use of AI in auditing?
- Can you explain any regulatory or compliance challenges you have faced when using AI in auditing?
- How do you think AI will affect future audit regulations and standards?

6.2 Corporate Culture

- Have you encountered resistance from colleagues or clients regarding the use of AI?
- Do you think AI gives larger audit firms a competitive advantage over smaller firms?

7. Job Security and AI's Role in Auditing

7.1 Perceived Threats and Opportunities

- Do you think AI will replace certain audit tasks or roles in the future? If yes, which ones?

- How has AI affected auditors' professional security and career opportunities?
- How do you view the relationship between AI and human auditors?
    - Do you see AI as a tool that supports auditors, or does it bring challenges to the profession?

8. Closing Questions

- Is there anything else about working with AI that you would like to add?
- Is there anything you have experienced or feel that we have not covered in the interview?
- Would you be available for a short follow-up interview of 10 minutes at a later date if new questions arise in the study?

7.3 Appendix 3: Revised interview guide in Swedish

Bakgrund och Erfarenhet

- Kan du beskriva din roll och dina arbetsuppgifter som revisor?
- Hur många år har du arbetat inom revision?
- Kan du berätta om dina kunder?
    - Vilken typ av kunder arbetar du oftast med?

1. AI i revision

- Kan du förklara hur du använder AI i din revisions/arbetesprocess?
- Inom vilka områden av revisionen ser du AI som mest användbart (t.ex. att identifiera risker, hitta bedrägerier, dataanalys)?
- Vilka förändringar har du observerat i revisionsprocessen på grund av AI-integration?
    - Kan du dela med dig av specifika exempel?
    - Tar AI/automation över de repetitiva arbetsuppgifterna?

2. AI i redovisning

- Hur har AI:s växande närvaro inom redovisning påverkat sättet revisionen genomförs?
- På vilka sätt har AI påverkat kvaliteten på finansiella rapporter, både positivt och negativt?

- Har du stött på situationer där AI-genererade finansiella data innehöll fel? Hur identifierades dessa och hur åtgärdades de?

3. Komfort med att revidera AI-genererad data

- Hur känner du inför att genomföra revision av finansiell data som har producerats med hjälp av AI?
    - Hur känner du inför att lita på AI-genererade revisionsresultat?
- Hur har AI påverkat din förmåga att tillämpa ditt expertomdöme/professionella åsikter vid revision?
    - Kan du beskriva en situation där AI-genererade resultat kolliderade med ditt professionella omdöme? Hur hanterade du det?
- Hur ser du på AI:s roll i att förbättra hastigheten och effektiviteten i revisioner? Ser du några avvägningar eller nya utmaningar?

4. Färdighetsanpassning och utbildning

- Vilken typ av utbildning har du fått om AI i revision, och hur har den påverkat ditt arbete?
- Vilken ytterligare utbildning eller stöd skulle hjälpa dig att känna dig mer säker på att använda AI i revisioner?
- Hur känner du att dina färdigheter behöver anpassas för att hålla igång med utvecklingen AI driver?
    - Behöver du nya färdigheter för att känna dig relevant och användbar?

5. Förtroende för AI-genererade finansiella data

- Hur skulle du jämföra ditt förtroende för AI-genererade finansiella rapporter med traditionella manuella revisioner?
- Vilka faktorer påverkar ditt förtroende (eller brist på förtroende) för AI-genererade data?
- Känner du dig trygg i det du gör och hur det görs?

- Hur tydliga är AI-genererade revisionsresultat för dig? Känner du att du kan förstå fullt ut hur AI kom fram till sina slutsatser?
- Hur tycker du att AI kan förbättra ditt arbete genom att ge mer detaljerade förklaringar om de steg eller logik som ligger bakom revisionsslutsatserna?
- Kan du berätta om ett tillfälle när AI-resultat var svåra att verifiera på grund av brist på förklaring?

6. Institutionella påtryckningar och AI-adoption

- Hur tycker du att samhällets användning av AI har påverkat eran implementering av AI?
- Tror du att ditt företag implementerar AI för att det är positivt för er eller pga standardiseringen av AI?
- Hur ser du på AI:s roll i framtida revisionsregler och standarder?

- Hur tror du att AI-adoption påverkar konkurrensen mellan stora och små revisionsföretag?
- Hur har dina kollegor eller klienter reagerat på den ökande användningen av AI? Har du stött på motstånd?

7. Jobbsäkerhet och AI:s roll inom revision

- Hur ser du på professionens framtid i närvaro av AI?
- Hur tror du att AI påverkar karriärutvecklingen och jobbsäkerheten för revisorer idag och i framtiden?
- Vad tycker du om de utmaningar AI kan medföra för mänskliga revisorer? Och vad tror du är de sätt att hantera dessa på?

8. Avslutande frågor

- Har du något mer som du vill tillägga om att arbeta med AI?
- Finns det några känslor eller erfarenheter som du tycker inte har uttryckts än i den här intervjun?
- Skulle du ha tid för en ytterligare intervju på 10 minuter senare för att ta upp ytterligare frågor som kan komma upp när denna studie har kommit längre?

7.4 Appendix 4: Original interview guide in Swedish

1. Bakgrund och erfarenhet

- Kan du beskriva din roll och dina arbetsuppgifter som revisor?
- Hur länge har du arbetat med revision?
- Vilken typ av kunder arbetar du vanligtvis med?
- Har du använt AI-baserade verktyg i dina revisioner? Om ja, vilka?

2. AI inom revision

2.1 Erfarenhet av AI-verktyg

- Hur ofta använder du AI-baserade verktyg i dina revisioner?
- Vilka typer av AI-verktyg eller programvara har du stött på i ditt arbete?
- Inom vilka områden ser du att AI är mest användbart i revision (t.ex. identifiering av risker, upptäckt av bedrägeri, dataanalys)?
- Har du märkt några förändringar i revisionsprocessen på grund av AI? Om ja, vilka?

3. AI inom redovisning

3.1 Erfarenhet av att granska AI-genererad information

- När AI används inom redovisning, hur skiljer sig granskning av AI-genererad finansiell data från traditionell revision?
- Har du märkt några skillnader i kvaliteten på de finansiella rapporterna på grund av AI?
- Har du stött på fel i AI-genererad finansiell rapportering? Hur hanterades de?
- Vilka utmaningar har AI medfört i revisionsprocessen, om några?

3.2 Bekvämlighet med att granska AI-genererad data

- Hur känner du dig kring att granska finansiell data som har producerats med hjälp av AI?
- Litar du på finansiella rapporter där AI har använts? Varför eller varför inte?

- Har AI påverkat din trygghet i ditt arbete?
    - Känner du dig säker i vad du gör och hur det görs?

4. Bekvämlighet med AI i revision

4.1 Upplevd påverkan på arbetsprocesser

- Känner du dig bekväm med att förlita dig på AI-genererade revisionsresultat? Varför eller varför inte?
- Hur har AI påverkat din förmåga att använda din expertis och professionella bedömning i revision?
- Anser du att AI förbättrar hastigheten och effektiviteten i revision, eller medför det utmaningar som motverkar eventuella effektivitetsfördelar?
- Har du varit med om situationer där AI gjort fel eller misstolkningar? Hur hanterade du det?

4.2 Anpassning av färdigheter och utbildning

- Har du fått någon formell utbildning i hur man använder AI i revision?
- Vilken typ av utbildning eller stöd skulle få dig att känna dig mer trygg i att använda AI i revision?

5. Tillit till AI-genererad finansiell data

5.1 Tillförlitlighet och noggrannhet

- Hur mycket litar du på AI-genererade finansiella rapporter jämfört med traditionell manuell revision?
- Vilka faktorer påverkar din tillit (eller brist på tillit) till AI-genererad data?
- Har du varit med om att AI:s resultat inte stämde överens med din egen bedömning? Hur hanterade du det?

5.2 Transparens och förklarbarhet

- Hur tydliga upplever du att AI-genererade revisionsresultat är? Kan du förstå hur AI kommit fram till sina slutsatser?
- Tycker du att AI borde ge mer detaljerade förklaringar om stegen eller logiken bakom sina slutsatser? Varför eller varför inte?
- Har du varit med om en situation där AI:s resultat var svåra att verifiera på grund av brist på förklaring? Hur hanterade du det?

6. Institutionella krav och AI-användning

6.1 Reglerings- och branschkrav

- Kan du beskriva eventuella krav eller förväntningar du upplever från tillsynsmyndigheter, branschstandarder eller din arbetsgivare när det gäller att använda AI i revision?
- Kan du beskriva eventuella utmaningar du har upplevt när det gäller att följa regelverk i samband med användning av AI i revision?
- Hur tror du att AI kommer att påverka framtida revisionsregler och standarder?

6.2 Företagskultur

- Har du mött motstånd från kollegor eller kunder när det gäller användningen av AI?
- Tycker du att AI ger större revisionsbyråer en konkurrensfördel jämfört med mindre firmor?

7. Jobbsäkerhet och AI:s roll i revision

7.1 Upplevda hot och möjligheter

- Tror du att AI kommer att ersätta vissa revisionsuppgifter eller roller i framtiden? Om ja, vilka?
- Hur har AI påverkat revisors yrkesmässiga trygghet och karriärmöjligheter?
- Hur ser du på relationen mellan AI och mänskliga revisorer?
    - Ser du AI som ett verktyg som stödjer revisorer, eller medför det utmaningar för yrket?

8. Avslutande frågor

- Finns det något annat kring att arbeta med AI som du vill tillägga?
- Är det något du har upplevt eller känner som vi inte har tagit upp i intervjun?
- Skulle du ha möjlighet att ställa upp på en kortare uppföljningsintervju på 10 minuter vid ett senare tillfälle om nya frågor dyker upp i studien?

7.5 Appendix 5: Interviewee table

Participant Nr	Level of auditor	Years of experience	Company size	Interview duration	Date
P1	Associate	2y	Big	40 minutes	2025-03-18
P2	Authorized, CEO	41y	Small	25 minutes	2025-03-19
P3	Associate	2y	Small	45 minutes	2025-03-20
P4	Associate	1y	Big	45 minutes	2025-03-19
P5	Associate	0,5y	Big	30 minutes	2025-03-24
P6	Authorized, team-leader	11y	Big	60 minutes	2025-04-08
P7	Senior Associate	10y	Big	50 minutes	2025-04-10
P8	Associate	1y	Small	20 minutes	2025-04-15
P9	Associate	2y	Small	60 minutes	2025-04-17
P10 & P11	Authorized & Associate	5y & 3y	Big	50 minutes	2025-04-23

7.6 Appendix 6: Interview coding

Code	Theme	Aggregated Dimension
P1: Using generative AI for support, not decision-making. P1: Utilizing generative AI for information retrieval. P2: Using generative AI as a 'ballpark' to develop ideas. P3: Using generative AI to learn about new professions. P4: Using chatbot specialized in auditing and accounting. P5: Automating repetitive, low-value tasks using generative AI. P6: Automation targeting anomalies instead of random sampling. P6: Using generative AI tools trained on fraud cases. P7: Data analysis being done by generative AI. P8: Limiting generative AI use to surface-level tasks. P9: Using automation for assessing client's documentation. P10: Using generative AI for support in decision-making.	Generative AI usage	Generative AI integration
P1: Enhancing fraud detection through generative AI. P2: Generative AI being better than humans at adding numbers. P4: Risk of generative AI exploiting loopholes. P5: Generative AI results conflicting with own professional judgement. P6: Generative AI reducing the number of errors as introducing new risks. P7: Generative AI generating different answers depending on the question. P9: Acknowledging that generative AI suggests wrong outputs. P9: Identifying more errors when auditing less tech-integrated firms. P9: Observing accuracy in system-generated summing.	Generative AI quality	
P1: Maintaining responsibility for audit conclusions. P2: Still needing humans for subjective judgements. P3: Believing humans still check everything. P4: Conducting more careful reviews of AI-generated reports. P5: Retaining human auditors for judgment and decision-making. P6: Maintaining manual oversight in high-risk scenarios. P6: Requiring human judgment to verify AI-generated results. P8: Emphasizing human accountability.	Human factor	

P9: Relying on auditor to handle deviations. P9: Evaluating human-generated reports as higher risk. P10: Humans still needed to make judgements.		
P1: Lacking transparency in AI-generated financial reports. P1: Trusting AI-generated data if trusted by clients. P3: Higher trust in audit-specific generative AI. P4: Addressing new transparency requirements for generative AI usage. P4: Difficulty in trusting generative AI without references. P5: Requesting generative AI to justify its conclusions. P6: Avoiding use of sensitive client data in generative AI models. P7: Having a hard time knowing what to trust from generative AI. P9: Applying professional scepticism regardless of tech use. P10: Needing tests to know the systems are trustworthy.	Trust	Generative AI perception
P1: Experiencing uncertainty around generative AI's output. P1: Recognizing positive responses due to generative AI's ability to improve efficiency. P3: Older colleagues struggling more with generative AI. P3: Has encountered false information from generative AI. P4: Facing uncertainties about generative AI's training and logic. P5: Further training on generative AI leading to confidence and trust. P7: Feeling confident in the work due to being able to ask colleagues. P7: Feeling uncomfortable with working with new tasks and technologies. P8: Adapting naturally to new tech.	Comfort	
P1: Maintaining multi-step review processes when using generative AI. P2: Needing to keep their professional scepticism. P2: Being more sceptical towards advice from generative AI. P3: Claiming scepticism is important whether it is AI or human generated. P3: Using generative AI puts more focus on being sceptic. P5: Reviewing AI-generated financial data cautiously. P6: Encouraging healthy scepticism toward machine-generated insights.	Professional scepticism	

P6: Requiring critical assessment and questioning of AI outputs. P7: Being more critical while viewing generative AI produced material. P8: Double-checking generative AI outputs. P9: Separating generative AI's technical help from professional judgment.		
P1: Acknowledging the need to keep up with other large firms to remain competitive. P2: Having to comply to regulations. P4: Acknowledging generative AI's role in making the industry more competitive. P6: Firms investing in generative AI to remain competitive in the industry. P7: Clients' digitalization forcing firm to adapt. P8: Anticipating market shifts. P8: Firms responding to societal adoption. P9: Shifting smaller clients form large firms to smaller firms. P9: Suggesting generative AI development begins in accounting before audit firms.	Institutional pressures	Future of profession
P1: Acknowledging that no one has lost their job due to generative AI. P1: Creating learning gaps for junior auditors. P3: Not needing as many auditors as generative AI takes over the time-consuming tasks. P3: Not needing as many associates due to generative AI. P4: Expecting generative AI to create new opportunities in auditing. P4: Making it harder to gain practical experience. P5: Facing reduced demand for junior auditors. P7: Believing careers won't be affected. P7: New hires not getting the same practical experience. P8: Perceiving limited impact of generative AI on career growth. P9: Potential job impact due to generative AI adoption without client growth. P11: Not worrying about being replaced.	Job security	
P1: Emphasizing the importance of learning new tools. P2: Thinking auditors will take on more contact with clients.	New skills	

P3: The competencies of auditors are changing to a more technical aspect. P4: Creating new types of tasks for employees. P4: Freeing up auditors' time for complex tasks. P5: Promoting upskilling to adapt to generative AI advancements. P6: Being expected to stay updated on ongoing generative AI updates. P8: Getting comfortable with generative AI though practice. P9: Adapting easily to tech due to age/experience. P10: AI freeing up time for other areas of specialties.	