Exploring the Challenges and Strategies of AI Adoption in Auditing: Insights from a Big Four Firm

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ABSTRACT,

Artificial Intelligence is slowly changing our life. Not only our life, but many industries have been exposed to AI and it is believed that this will only continue in the near future. This trend is also seen in the field of auditing. Big Four accounting firms have made many substantial investments into AI, recognizing its massive potential. Due to the nature of auditing which consists of many structured and repetitive tasks, and challenges in analyzing the amounts of structured and unstructured data, it is an ideal candidate for the application of AI. In reality, AI is still far away from being fully adopted by auditors. A need was identified for a better understanding of auditor's challenges regarding AI Adoption. Given this need, this paper therefore aims to find out what challenges auditors face when adopting AI technologies within a Big Four firm. The interview guideline incorporated the Technology-Organization-Environment Framework, shaping the research approach. Research was directed through a qualitative approach with semi-structured interviews. Through the interviews with experts in the field, this study obtained first-hand knowledge on the challenges auditors face when adopting AI in their practices. Finally, this study contributes to the existing body of knowledge on AI adoption under auditors by providing a clear overview of the different challenges auditors face per overarching dimension of the Technology-Organization-Environment Framework.

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Keywords
Artificial Intelligence, AI adoption, Audit, Big Four, TOE framework, Information Technology.

1. INTRODUCTION

Following years of disappointment during ''AI Winters,'' diverse sectors of business are witnessing the arrival of AI's ''Spring'', with its substantial advantages (Issa et al., 2016). The development of information technology (IT) has been evolving rapidly. Evidence can be found in the corporate sector, where traditional practices are shifting towards a future where digital intelligence plays a role. Seventy-five percent of 816 corporate executives surveyed in the *2015 Deep Shift: Technology Tipping Points and Societal Impact* reported that 30% of corporate audits will be performed by Artificial Intelligence in 2025 (Global Agenda Council on the Future of Software & Society, 2015). Corporation's financial statements are used by many different stakeholders, including shareholders, creditors, staff, and tax authorities for business decisions. These internal and external stakeholders need credibility when making these decisions, while corporations may depart from the appropriate accounting standards, such as the IFRS and GAAP, due to unintended errors, lack of knowledge, human bias or even deliberate falsification which results in an unfair view of their financial performance (Whittington & Pany, 2021). Audits are thus necessary to reduce the information risk stakeholders have when making business decisions. Audits are held by an independent party who reviews the financial statements of an organization to assess their alignment with the accounting standards required (Whittington & Pany, 2021). If the auditors review the financial statements and come to the conclusion that the corporation has not materially departed from the accounting standards required, an audit report will be prepared that states that the corporation presents an objective view on their financial performance (Whittington & Pany, 2021). The use of Artificial Intelligence is an important evolvement in the field of accountancy and auditing (Damerji & Salimi, 2021). Due to the nature of auditing which consists of many structured and repetitive tasks, and challenges in analyzing the amounts of structured and unstructured data, it is an ideal candidate for the application of Artificial Intelligence and data analytics (Kokina & Davenport, 2017). Repetitive tasks that were usually performed by humans are now becoming automized, to enable auditors with more time on tasks that require professional judgement. (Handoko et al., 2018; Huang & Vasarhelyi, 2019; Thottoli et al., 2022). The use of information technology in audit has been crucial in the process of enhancing audit quality and efficiency (Curtis & Payne, 2008). The rise of Artificial Intelligence in audit has enhanced accuracy and data quality (Zhang et al., 2020), improved decision-making by analyzing substantial amounts of data (Kopalle et al., 2022) and reduced errors in the evaluation process of financial data (Vărzaru, 2022), to name a few advantages. The Big Four accounting firms have recognized the advantages AI can potentially deliver, resulting in substantial investments in the technology (Issa et al., 2016). While the (potential) advantages seem clear due to the growing literature on the usage of AI in audit, Hashid and Almaqtari (2024) mention that the obstacles and barriers on AI adoption in the audit deserves further research. Seethamraju and Hecimovic (2020) argue that research on the adoption of AI is still very limited since most publications highlight the potential of AI in the audit and are descriptive of nature, ignoring its adoption challenges. Due to the research on AI adoption in auditing being quantitative, there has been even less research on the qualitative factors such as perceptions, attitudes, and concerns of auditors related to the adoption of AI that results in challenges.

Furthermore, there has been no empirical research on the challenges of AI adoption in the audit practice in the Netherlands, especially in a Big Four firm. Thus, research of qualitative nature about the challenges of AI adoption in auditing, with insights from a Big Four firm from the Netherlands would benefit auditing firms with setting strategies for the allocating of their resources due to the significant investment required for the implementation of AI in their practices. The following research question is formulated to identify the gap of knowledge around AI adoption in audit:

What challenges do auditors face when adopting AI technologies at Big Four firms?

This research aims to fill this gap and provide audit firms to understand the challenges that influence AI adoption in audit companies and suggest strategies. Furthermore, Gotthardt et al. (2020) argue how AI adoption is in its very early stages: only five percent of companies consider themselves mature in their use of AI, while indications on the use of AI in audit are very promising in the foreseeable future. This paper contributes to the limited research done by exploring the challenges influencing auditors in their adoption to AI, which will help audit firms in their practical implementation.

2. LITERATURE REVIEW

The available research provides well-known literature on the advantages and risks associated with the integration of AI in auditing. It addresses the concerns and factors around the adoption of AI in audit, and the limited research that has been done on it. Furthermore, it proposes a framework which is used as a theoretical lens for the formulation of the interview guideline.

2.1 AI in Audit

Accounting and auditing serve as vital pillars that uphold the reliability, credibility, and financial stability of a corporation. By offering unbiased assurance, they contribute to market trust which plays a role in the overall health of the economy (Feliciano & Quick, 2022).

Traditionally, these fields relied heavily on manual procedures and human expertise. However, with the rise of information technologies coupled with increasing competitiveness and more complex datasets, a significant transformation in these fields has occurred. Artificial Intelligence is a computer system that can transform human intelligence into productive work through technology (Al-Sayyed et al., 2021). AI technologies make machines "intelligent" by utilizing automation to imitate or enhance human intelligence, aiming to enhance analytical capabilities and decision-making abilities through technology (Mihai & Dutescu, 2024). Within the subset of AI, machine learning (ML) and robotic process automation (RPA) are the most used techniques in audit (Bakarich & O'Brien, 2021). These techniques are implemented in processes where fraud detection, forecasting and prediction play a role. This is due to the growing volume of data leading to complex processes where the traditional manual procedures are not as efficient anymore.

RPA is a technique that can perform routine business processes by automating the way people interact with multiple applications

(Huang & Vasarhelyi, 2019). It is ideal for tasks that are standardized, repetitive and mature such as internal control testing and detail testing in the audit (Huang&Vasarhelyi, 2019; Lacity et al., 2015). With RPA, audits can be performed more accurate due to less human error (Dahiyat, 2022). RPA can analyze all the datasets involved with the transactions that are tested, instead of the traditional sampling method, and leave the outliers and anomalies for the auditor as these are more high-risk areas and are therefore in need of closer examination by the auditor. With RPA, auditing does not change radically as human judgement and expert skepticism is still necessary for a successful audit (Dahiyat, 2022). ML can help auditors by recognizing and applying trends and derive algorithms based on these trends and further feedback (Han et al., 2023). This helps the auditor with decision-making based on the data fed. Regardless of AI's potential in the audit, it is still labor intensive due to the tools mostly focusing on automating a specific task. This provides the auditor with another task, which is to incorporate these different tools into their audit practice. The need of integrating these different systems and applications, as it is not applicable in every situation, creates additional work (Huang & Vasarhelyi, 2019). To increase the ability of RPA, which gives it the possibility to handle more complex tasks, it can be combined with ML (Huang & Vasarhelyi, 2019).

AI can be seen as an opportunity, since it can take over the repetitive and structured tasks from auditors, such as business analysis and external reporting, giving them time to focus on more value creating activities that require professional judgement (Kokina & Davenport, 2017, Gonçalves et al., 2022, Kend & Nguyen, 2020). While the potential advantages of AI in the field of audit seem clear, various risks are also identified. Inaccuracies in the input data, potential human bias, incomplete data in the AI solutions and unclear interpretation of the results leading to difficulties (Brynjolfsson, 2022, Big Four, 2023). After all, the role of the auditors is to provide reliable and credible assurance of the corporations they audit (Feliciano & Quick, 2022). By solely focusing on the advantages of AI, companies underprioritize the ethical and resilience issues that need to be considered (Big Four, 2023). It is no surprise that new information technologies such as AI are being invested in by audit firms (Omoteso, 2012), the literature presents a compelling view of the future of AI in auditing. However, literature also presents risks and ethical considerations due to the integration of AI, which emphasized the need for a balanced approach.

2.2 AI Adoption in Audit

The integration of IT tools in auditing has been an ongoing process for some time now.

Audit firms have utilized electronic data processing, computer-assisted audit techniques (CAATs), since the 60's (Kend & Nguyen, 2020). The automation, through CAATs, of structured audit tasks resulted in improved efficiency and audit quality (Curtis & Payne, 2008). However, traditionally seen, auditing has been a late adopter of new technology, while the labor-intensive nature and competitive pressures make it an ideal candidate for automation (Issa et al., 2016). The adoption of IT tools is relatively low for several reasons. These include lack of confidence and knowledge (Braun & Davis, 2003; Ahmi & Kent, 2012), lack of clear guidance and instructions on the use of IT tools (Eulerich et al., 2021), lack of explainability (Ali et al., 2023), poor client systems, extent of organizational pressures and infrastructure (Bierstaker et al., 2014), reluctance of auditors to change and preference for Excel (Pedrosa et al., 2019), data security issues and limited knowledge of the implications around the use of IT tools (Issa et al., 2016) and lack of trust in the IT tools (Janssen et al., 2020). While we can gain valuable insights into implementation challenges from the existing IT literature in audit, it is necessary to recognize that AI implementation presents its own unique set of challenges, that need further investigation. Due to AI's unique features, the existing IT literature does not fully apply to this technology (Veale & Brass, 2019). Therefore, researchers call for studies on the unique factors that are related to the implementation of AI, since it is still poorly understood (Maragno et al., 2023).

Goto (2023) argues how recent studies have identified factors that positively influence the adoption of AI, but there are only a few studies that have addressed the challenges of adopting AI and how to manage the process, which adds to the existing knowledge in practice and theory on AI adoption in the professional service industry. The adoption of AI has therefore been addressed at different levels in the organization, such as teams, business units or whole organizations (Pateli et al., 2020). Recent research on the replacement of auditors by AI has shown it to be ''long way off'' due to the requirement of understanding the client's business, its risks, compliance with standards and exercise of professional skepticism (Kend & Nguyen, 2020). While AI will not (for the foreseeable future) replace auditors, it will significantly change the role of the auditor and how audits will be performed in the future (Wassie & Lakatos, 2024). Hence, researchers and practitioners need to collaborate more to shed light on this transition (Kokina & Davenport, 2017).

2.3 Theoretical Framework

Numerous theories and models have been put forth to examine the adoption of innovative technologies (Oliveira & Fraga, 2011). Amini & Bakri (2015) identified nine theories in this field; theory of reasoned action (TRA), the technology acceptance model (TAM), the motivation model (MM), the theory of planned behavior (TPB), the combined TAM and TPB (c-TAM-TPB), the model of PC utilization (MPCU), social cognitive theory (SCT), the diffusion of innovation theory (DOI) and the Technology-Organization-Environment Framework (TOE). These theories and models can be applied to the adoption of AI at either the individual level or firm level. In this research, AI adoption will be studied in a Big Four firm, so the TOE framework will be applied, which is a well-known framework in the adoption of technology on the organizational level.

2.3.1 TOE Framework

TOE is a firm-level adoption framework that was developed by Tornatzky and Fleischer (1990). The TOE framework explains how not solely technical factors are influential in the adoption of innovational technologies, but organizational and environmental factors play a role too (Baker et al., 2024).

The technological dimension describes the internal and external technologies relevant to the Big Four firm. These are the current technologies at the firm, but also the external technologies available on the market (Baker, 2011).

Organizational dimension refers to descriptive data of the Big Four firm such as size and its managerial structure and hierarchy. The environmental dimension is the field in which our Big Four firm operates mostly, and its competition and relationship with the government, thus audit in our case (Oliveira & Martins, 2011).

According to Zhu et al. (2003), the TOE framework is extensively used in the IT literature to explore adoption factors. Oliveira and Martins (2011) have stated that the TOE framework is appropriate to research the adoption of new technologies such as AI, which is relevant to us.

Combining recent literature on the TOE framework in IT adoption (Seethamraju & Hecimovic, 2020; Wassie & Lakatos, 2024, Krieger et al., 2021) with the holistic and flexible perspective the TOE framework offers on it, it is suitable for our research due to our exploratory approach (Yang et al., 2024). Furthermore, there is an increasing interest on literature that uses the TOE framework in the implementation phase of IT tools (Pateli et al., 2020).

In this research, where I explore the challenges of AI adoption in a Big Four firm, the TOE framework is relevant due to the technological intricacies of AI, organizational dynamics of an audit firm and the broader environmental context where the firm operates.

3. METHODOLOGY

3.1 Research Design

This research uses an explorative, qualitative methodology to investigate the main challenges of the auditors in the Big Four firm in the adoption of AI, and how these challenges are mitigated. I collect data through 11 semi-structured interviews with both auditors and IT-auditors of the Big Four firm in the Netherlands, from different levels in the hierarchy of the firm to get a better understanding of the challenges throughout the wide range of insights and experiences gathered. As part of the data collection, online documents and reports were studied to ensure triangulation (Natow, 2019).

To ensure a holistic representation of perspectives on AI, the selection of participants span a wide range of work experience, age, and gender. This approach's aim is to gather diverse insights and experiences, thereby enriching the findings of the data collected. I followed the recommendations for qualitative interviewing given by Myers and Newman (2007) and attempt to avoid the problems that the authors described.

Due to the new nature of AI in the audit, the interviewees required time to prepare for the interview topic, so the interview guideline was sent to the interviewees in advance and the interview is conducted with it. The purpose of sending the interview guideline in advance was to create familiarization with the guideline and thereby enhance the quality of responses during the interview. Throughout the interviews, comments were noted on what can be improved in the interview guideline and the way of interviewing in order to get optimal results and information from further interviews. Finally, the data analysis is guided through Gioia's systematic methods of analyzing qualitative data. (Gioia et al., 2012).

3.2 Data Collection

The interview guideline is based on online documents and reports discussing the use of AI in the firm's audit department combined with the TOE framework which is used as a theoretical lens and structure for the interview guideline. Creation of the guideline started with identifying key constructs based on a review of relevant literature on the adoption of AI. These constructs were selected per dimension, resulting in full coverage of the relevant technological, organizational, and environmental factors. The interview guideline is structured as followed: 4 general questions as a warm-up, 4 questions related to the technological dimension, 4 questions related to the organizational dimension and 3 questions related to the environmental dimension. Full guideline can be found in the appendix. In the end, general questions were asked based on the challenges mentioned, to explore strategies on how to overcome them. The guideline questions and follow-up questions related to the technology dimension were linked to the characteristics of the AI-tools and perceived advantages and disadvantages of integrating AI in their work. Questions regarding the organizational dimension linked to the size and structure of the firm, top management and leadership support in the firm, available resources in the firm and the organizational culture. Additionally, for the environmental dimension, questions were linked to industry readiness and related barriers specific for the audit industry, industry regulations and standards specific to a Big Four auditor, client expectations and client readiness for AI. Data is gathered through interviews with 11 auditors and IT-auditors in the Big Four firm (See Appendix for the full sample of interview participants). 6 of the 11 participants in our research are Registered Accountants (RA), which is the equivalent of a Certified Public Accountant. Registered Accountants are registered at the ''Netherlands Institute of Chartered Accountants'' (*Registration And Consultation Accountants' Register*, z.d.). 2 of the 11 participants are Registered EDP-auditors (RE). Registered EDP-auditors are qualified IT-auditors that are registered at the ''Nederlandse Orde van Register EDP-Auditors". These participants have specific expertise in the field of IT and the implementation of IT in the audit (*Registration And Consultation Accountants' Register*, z.d.). 2 of the 11 participants are nearly finished with their Post-Master Accountancy and will collect their RA title soon enough. 1 participant possesses both the RA and RE title.

The participants in our case are thus well qualified and cover both expertise in audit and IT-audit.

These participants have specific expertise in the field of IT and the implementation of IT in the audit (*Registration And Consultation Accountants' Register*, z.d.).

Having a research internship at the firm allowed me access to the participants. Interviews are transcribed fully through an online software called Amberscript. The average interview duration was 33 minutes. Interview transcripts can be shared upon request. The decision to utilize the interview method as data collection method is guided by the objective of gaining a comprehensive understanding of challenges in AI adoption in the Big Four firm under the auditors. This method allows for the collection of the individual's interpretations of AI and its implementation process (Orlikowski and Gash, 1994). The interviews are semi-structured, which gives us a balance between structure and flexibility. Semi-structured interviews include a mixture of both open-ended and close-ended questions, as well as follow-up questions that are not part of the script (Adams, 2015). The main reason semi-structured interviews are an appropriate choice for data collection in this research is that they help the researcher with exploring unknown themes due to its flexibility. This flexibility is not only helpful for uncovering theoretical insights about the challenges of AI adoption, but also for the practical side. Allowing participants to give broad answers can result in new leads for further research in this study (Adams, 2015). The population consists of auditors, who use various AI-tools in their work and IT-auditors that have extensive knowledge on the implementation of these AI-tools. Therefore, a purposive sampling approach is followed since participants are chosen who meet certain criteria (Guest et al., 2013) (Table 2). Purposive sampling allows for the identification of the participants who are most likely to contribute valuable insights to the research (Guest et al., 2013). This approach is particularly relevant since the research is being carried out within a specific Big Four firm, where employees are well-positioned to identify those among them who possess the most knowledge on the subject of AI, and its adoption. This ensures that the data collected is relevant and rich in detail which results in a more insightful study. When referring to statements made by participants in this paper, an abbreviation of the function with the number of the participant is used.

Image 1. Criteria for selecting interview participants.

Criteria
1. Participant had to be employed by the Big Four Firm in the Netherlands.
2. Participant should have at least 4 years of work experience in the audit industry.
3. Participant should have experience with various AI-tools in their audit practices.

3.3 Data Analysis

As stated previously, the data from the semi-structured interviews is coded and analyzed through Gioia's methodology. Coding is done through an online software, Atlas.ti. Our inductive approach in this research makes Gioia's methodology a fit (Gioia et al., 2012).

This method is a widely used approach "designed to bring 'qualitative rigor' to the conduct and presentation of inductive research" (Gioia et al., 2013, p. 15). Furthermore, it allows for a systematic approach where a deep understanding of informants' experiences are considered (Goto, 2023).

The Gioia methodology is a way of coding, analyzing, and reporting of the data gathered from the interviews. The method consists out of three phases. In the first phase, the collected data from the interviews is read line by line, where key coding elements are identified resulting in the first-order codes. Inductive codes are created that resemble the participants answers. After filtering out irrelevant codes, 238 unique first-order concepts were formed. In the second phase, similarities and differences among the first-order codes are looked for, creating a smaller, second-order themes set. The aim of the second phase is to look for themes which suggest concepts that create more clarity around the observation of the interviewees under the three overarching dimensions: technological, organizational, and environmental. In total, 6 second-order themes were left. Once these second-order themes were found, the third and final phase arrived. This phase involves further refining of the existing themes into a smaller number of third-order aggregate dimensions. These dimensions may be new concepts in the relevant literature, or existing concepts from different areas of research. These dimensions form the foundation for the data structure, which will be a visualization of the coding progression and aids with understanding the relationship between the codes. After further refinement, 3 third-order aggregate dimensions were formed. By analyzing all three orders of code with the structure of the TOE framework, our research question can be answered by elaborating on the main challenges for the auditor when adopting AI per aggregate dimension. Before explaining the data structure, I'd like to emphasize first that the participants of the interviews may have given answers that do not directly relate to AI-tools, but instead a different technology. To prevent this, several steps were taken. First, participants of the interview received an information letter on the subject alongside the interview guideline to prepare. Second, participants received a verbal explanation at the beginning of each interview which consisted of asking the participants to solely give answers related to AI-tools used in their audit practice. All participants demonstrated a solid understanding of the AI-tools available at the Big Four firm since they stated correctly which tools are mainly used at the firm and for what tasks. Third, interviews were conducted with IT-auditors to see if their answers regarding the challenges of AI adoption were similar compared with the answers of the auditors. Many, though as expected, not all, were similar. Nevertheless, it is still possible that answers given regarding the challenges of AI adoption were irrelevant towards our research. These answers, when noticed, were not included.

3.4 Case Description

Research is conducted at one of the Big Four firms. The Big Four firms are PwC, Deloitte, KPMG, EY (Elbra et al., 2022)

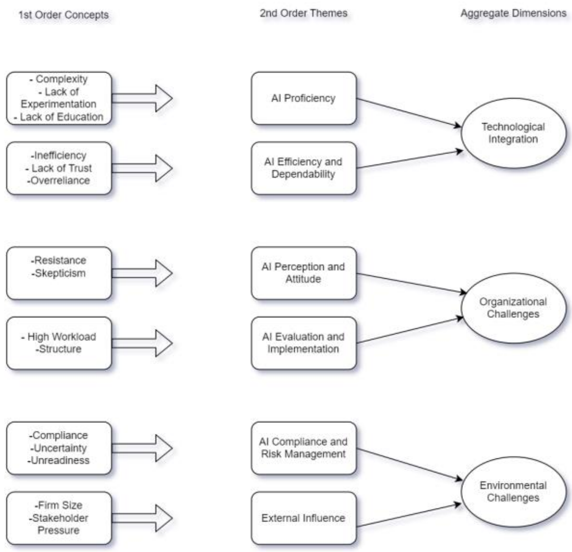
The Big Four firm in question is a leading multinational professional service firm that provides a range of services including audit, accounting, financial advisory, consulting, tax services and more. In our case, research has been conducted in the assurance and audit department due to the high potential and exposure of AI implementations in their practices (Damerji & Salimi, 2021). Research is conducted in the Netherlands where auditors have been getting introduced to more and more AI implementations recently, leading to a suitable environment for the research. For the purpose of this study, the firm will be referred to as ''Firm SC''.

Firm SC has been awarded multiple awards due to their extensive investments into AI recognizing its potential for the next generation audit (Firm SC, z.d.). It has invested in Amber, which is a predictive analytics tools that is used by auditors to predict client revenue by integrating cloud-based Machine Learning capabilities with advanced statistical models. Amber allows auditors to work more efficiently, while simultaneously increasing the audit quality by having built-in data reliability and model validation checks when testing a set of transactions of a line item on the financial statement (Firm SC, z.d.). Tool ''FRIO'', which was recently implemented, helps auditors with reviewing financial statement disclosures. FRIO uses AI capabilities to allow the auditor to review large volumes of data quicker and more accurate giving them time to focus on more complex and human judgement-intensive tasks. FRIO is useful since it takes over a task that is time-consuming and prone to errors when done manually. On the other hand, the data needs to be standardized to a certain level for FRIO to be applicable (Firm SC, z.d.). Last relevant tool in our case is ''ChatVEL". ChatVEL is a Generative AI that helps auditors as an intelligent AI assistant by responding to questions within a secure environment due to auditors being heavily exposed to confidential information in their practices. Time-consuming but relevant tasks for an auditor such as: Summarizing Management Reports, Accountant Reports or specific Audit Guides can be generated by their chatbot, ChatVEL. ChatVEL helps the auditors by minimizing human error in time-consuming tasks by providing reliable and accessible output. This allows the auditors to allocate more time on complex work that requires their human judgement (Firm SC, z.d.). The use of these tools varies a lot per level within the Big Four. In audit firms, there is a clear structure and separation of tasks, which is important to understand correctly. Associates and Senior Associates carry out most of the steps in an audit which are: gather required input from client, do general testing, conduct research on accounting standards and regulations and more tasks that are less complex and require less human judgement. Managers generally review the work that the (Senior) Associates have performed as their tasks are more focused on project management and supervision. They perform more complex tasks, which require more human judgement and expertise. Finally, partners review the file again but on a higher level as they are responsible for the overall management and strategic decision-making. Partners are also responsible for signing off the final audit report. These tasks are not repetitive and require an even higher level of human judgement and expertise. What one must understand is that the use of AI in the audit differs across hierarchical level, since increased human judgement directly relates to less AI integration within accounting firms (Munoko et al.,2020).

4. RESULTS

As described in chapter 3, 11 interviews were held at the Big Four firm to gather insights about the challenges experienced when implementing AI in the audit practice. This section discusses the challenges by category and sub-categories. The categories are shown in the data structure below. The challenges are categorized and provide in such manner a clear overview of the challenges auditors face per overarching dimension of the TOE framework. The results are discussed in the following sections.

Image 2. Data Structure Visualization.



Note. Own work.

4.1 Technological Integration

First of all, challenges related to the technological dimension of the TOE framework are identified. Technological integration as a dimension consisted of 110 unique first-order concepts. After refinement, 2 second-order themes were left: AI Proficiency, and AI Efficiency and Dependability. As overarching dimension, Technological Integration represents the challenges auditors experience when adopting AI tools in their audit practices due to the characteristics of the technology itself, such as complexity, compatibility, and ease of use.

4.1.1 AI Proficiency

For auditors, it is important to understand how AI can assist them in their job. Due to the (assumed) complexity of AI, lack of experimentation with AI and a lack of education on AI, 4 of the 11 participants feel not proficient enough to use AI in their practices. Lack of education (8 of 11 participants) is the most common factor. While participants mention that training on the use of AI in the audit is available, this training is very general. SA4 mentioned when asked about what is necessary for acquiring knowledge: *Specific trainings, involvement of top management, and the opportunity to innovate. I think those are the most important things.* To understand and be confident in the output of the AI-tool, one must first understand how AI can be used to enhance their work. When questioning whether auditors have the possibility of experimenting with AI, M3 mentions: *This is a good question. The firm does not want any mistakes to be made. Simply because the consequences can be vital for the firm. On the other hand, mistakes also damage the reputation of our profession, which is our right to exist. Supervisors have created a sort of culture of fear due to multiple reviews and fines. This affects the auditor with their adoption to innovation.* Due to the culture of fear, auditors fear the use of AI in an environment where mistakes cannot be made. Thus, a space where experimentation can take place in a safe environment, is crucial for the auditor to gain confidence in using AI. The lack of this ''safe space'' poses a challenge for the auditor to integrate AI in their practices. Furthermore, an audit is seen as a team effort. There is a clear separation of tasks, where cooperation is crucial for achieving success. The complexity of AI is perceived different per function in this Big Four firm. When applying AI in the audit report, the output needs to be understandable for every auditor working on the case. Due to a difference in task responsibilities between managers and (senior) associates, less attention is given to AI-tools by managers, which creates challenges for the (senior) associates when applying AI. SA5 stated: *One time I had a manager that did not know how the AI-tool worked. I used the AI-tool in my work and added my part to the audit report, which he removed afterwards.* The advantages of AI applications in the audit are perceived differently per level in the firm, which creates cooperation problems for the team when working on an audit report. The managers and partners prefer AI for reporting, rewriting and translation purposes, as AI seems to be in a ''to early'' stage in the firm to make important decisions. This is due to a higher perceived complexity with managers and partners compared to (senior) associates, since they believe that their work is not standard and requires a high level of human judgement. Furthermore, they express that the value of AI in the audit is not directly related to AI-auditing, but more in regard to the reporting and documentation activities of the audit report. M2 states: *I do not think that the most value of AI is in AI-auditing. If I look at an audit client which gave us 1500 hours to complete the audit, 800 hours go into planning and completion tasks. This is already half of the audit. The other half is where you work with the numbers. With these numbers, again 50% goes to simply documenting what you have seen. The testing tables are necessary to be checked by the auditor. AI can help with proposing a quicker way of analyzing it, but it needs to be checked manually. On the other hand, a management letter and accounting report took me 80 to 100 hours to finish in the past. With the help of ChatVEL, it has been halved*. Thus, the relative advantage is perceived different by managers in comparison with (senior) associates. This can lead to managers and partners underutilizing AI-tools for auditing purposes, leading to poor data inputs which reduce the effectiveness and accuracy of AI. Lack of experimentation in a safe space, lack of education on practical cases and perceived complexity of AI result in challenges for the auditor to reach AI Proficiency.

4.1.2 AI Efficiency and Dependability

Speed is a critical factor for audit firms and auditors for several reasons. It is not only related to completing tasks quickly, but also about enhancing productivity, meeting tight deadlines, and maintaining a competitive edge on the audit firms. Audit firms are in the professional service industry, where client satisfaction is crucial. The clients in question have strict deadlines for the financial reporting, and auditors must complete their work before the deadlines to maintain their reputation as reliable and efficient. If AI takes longer to perform audit tasks compared to the traditional methods, a dilemma occurs as auditors have the choice between the manual method which is more efficient and ensures keeping the deadline, while AI may give a better depth of analysis but causes delay. This dilemma proposes a challenge for the auditor. M2 states: *When you integrate AI in your audit, there are so many prerequisites that need to be met, that you are faster and more efficient when sticking to the traditional method.*

When an external review is held, and you have worked with AI, they will ask for 300 difficult questions that you would not encounter if you would stick to the traditional method. This is due to a lack of trust from the external reviewers. For example, when the auditor does an audit test, which is a procedure performed by auditors to gather evidence about the corporation's financials, many prerequisites need to be met to ensure the audit quality. M2 continued with: *When using AI for testing, it becomes quickly inefficient. When you test through the traditional method, you take a sample manually. Let's say, 20 receipts. The chance of outliers is relatively small, and if you get one, you only have to resolve the problem with 1 receipt. When testing is done with AI, it analyses the full population sample, where 1% deviation is significantly harder to figure out since the sample size is bigger and it is harder to analyze, which costs more time.* Therefore, the challenge for the auditors lies in managing the balance between embracing the new AI-tool which enhances the audit quality but may be inefficient, and the traditional method which gives you a less comprehensive analysis but is trusted more by external reviewers and may be more efficient. The lack of trust does not only play a role for the external reviewers. Auditors from the Big Four Firm recognize it too. 9 of the 11 participants state that they are not confident in AI, in regard to making correct decisions. M3 states: *The output from the AI is solely based on our own Big Four data. With no confidential data and data from other firms, the output can be biased and of less value.* The main reasons why the participants do not (fully) trust in the AI-tools is due to a lack of explainability, that results in the fear of wrong output, fear of confidential data that gets leaked and the fear of the unknown. Furthermore, 5 of the 11 participants state that becoming too reliant on AI, would result in becoming less creative and critical. Being critical is an essential skill for an auditor since it is necessary for identifying risks and problem-solving. By becoming overly reliant on AI, auditors may accept the outputs generated by AI without applying further due diligence themselves, which could lead to complacency. For the auditors, the main challenges in adopting AI in this category are AI being inefficient due to extreme prerequisites, lack of trust due to the fear of using wrong output, lack of explainability about the AI, and the fear of becoming over reliant on AI. Auditors must see an AI-tool as a reliable, secure, and efficient tool for it to be adopted. At the moment, uncertainties around AI due to its complexity pose as challenges for the auditors.

4.2 Organizational Challenges

Secondly, challenges related to the organizational dimension of the TOE framework are identified. Organizational challenges as a dimension consisted of 46 unique first-order concepts. After refinement, 2 second-order themes were left: AI Perception and Attitude, and AI Evaluation and Implementation. As an overarching dimension, organizational challenges represent the challenges auditors experience when adopting AI-tools in their audit practices. The organizational challenges refer to the internal context in which the technology is used, such as the firm's size, structure, organizational culture, and top management.

4.2.1 AI Perception and Attitude

Skepticism towards AI-tools concerning the effectiveness and reliability brings doubt. This can cause auditors to be hesitant when AI-tools are available, which in turn can slow down the integration process. There is a clear difference in perception towards the AI-tools that are introduced in this firm. The more complex the task, the longer and more it takes to adopt AI under auditors. The perception under auditors towards the chatbot is different than towards the predictive analytics tools. This due to the difference in complexity, performed by the AI-tool. 3 of the 11 participants mention to be skeptic about the effectiveness of AI when it gets complex and professional judgement is needed. P1 states: *I do think that when you are dealing with a lot of data with low complexity and high standardization, AI is suitable for that. But if the data is complex and requires professional judgment, I am curious about what could be done with it. It might be possible, but I am currently skeptical about that. Keep thinking critically yourself, but that is also the danger of not using it, because by just being skeptical, you will also use it less.* Skepticism is necessary for an auditor since they are trained to approach their work with a questioning mind and a critical view. While this helps when assessing audit evidence for example, it works counterintuitively in the integration process of AI-tools, which poses a challenge for the auditors. The organizational challenge here is to create the right level of skepticism for the auditors in the firm, that keeps the critical eye while being open to new AI integrations. Resistance is another major challenge. 7 of the 11 participants mention that change is needed when adopting AI-tools, but that the auditor does not like to change. P1 states: *auditor as a type is by definition someone who likes to conform to rules and is a bit more reserved to change.* The individual and cultural resistance at this Big Four firm hinders the adoption of AI due to their risk-averse behavior and deeply rooted traditional way of working. While participants acknowledge support from top-management and leadership, it is seen as abstract and slow of pace. To add, SA4 states: *Well, I think it's difficult, because it is a large office, that you sometimes feel less connected when something is introduced at a high level.* Due to the size of the organization, it has challenges in change management due to the complexity of coordinating initiatives across different departments and business units. This creates challenges for the individual auditor due to feeling detached and reduced commitment leading to higher resistance.

4.2.2 AI Evaluation and Implementation

6 of the 11 participants mention the high work pressure that they are under, resulting in less time for acquiring the necessary skills that are needed for using AI in their practice. This results in them doing the audit in the traditional way, instead of opting for the new possibilities. SA1 mentions: *Yes, I think that because the workload is very high and I talk more from my experience, there is just less time to really work on it.* This creates a circle that does not end. On one side, especially junior, auditors would like to use AI in some of their practices since they are convinced that it is more efficient, while on the other side, the auditors feel that they have a too high workload, to focus on how to implement AI in some of their practices. The pressure of tight deadlines leads to prioritization of immediate tasks instead of long-term innovation with the adoption of AI. Furthermore, 9 of the 11 participants see the structure of the Big Four firm as a challenge. Due to rigid hierarchies, centralized decisions, and a lack of collaboration between external business units and internal departments, challenges are formed for the individual auditor. The hierarchy and structure of the Big Four firm is clear, with a separation of tasks and responsibilities at every level. M3 states*: I think it all goes slower because we are a very large organization. So, I think it will take quite a bit of time and effort to fully integrate that into our processes, as we need to get a very large crowd of people on board to start applying AI.* Thus, it is important that the auditor does not only embrace AI, but also plays an active role in change management. 10 of the 11 participants state that they either have no interaction about AI with colleagues in a stimulating way, or they have to initiate the interaction. Auditors are challenged due to a lack of a stimulating environment, where they must work harder to build advocacy for AI.

4.3 Environmental Challenges

As last, challenges related to the environmental dimension of the TOE framework are identified. Environmental challenges as a dimension consisted of 82 unique first-order concepts. After refinement, 2 second-order themes were left: AI Compliance and Risk management, and External Pressure. As an overarching dimension, environmental challenges represent the challenges auditors experience when adopting AI-tools in their audit practices. The environmental challenges refer to the external context in which the audit firm operates, such as regulatory requirements and client needs.

4.3.1 AI Compliance and Risk Management

7 of the 11 participants see being compliance-driven as a challenge when adopting AI, especially in a Big Four firm. Auditors must adhere to a range of compliance requirements to ensure integrity, objectivity, and professionalism. The external regulation, such as the NV COS, consists of setting standards, implementation of these standards in practice, monitoring of compliance and enforcement procedures. NV COS is the standard compliance guide that every audit firm must adhere to. It contains a lot of steps that have to be taken before an auditor can use the data output from AI as control-information.The regulation of audit is there to ensure that auditors follow best practice standards and work independent. This to maintain a good reputation and avoid heavy fines or penalties. The Big Four firm adheres to the standard compliance requirements, but has implemented additional compliance measures, which propose extra challenges with the adoption of AI under auditors. SM1 states: *AI adoption also slows down because look, we have the NV COS which contains quite a few things about compliance standards. Inside our Big Four firm, we have made it an art to be even stricter than NV COS. You see several topics in which NV COS is a bit easier to deal with compared to our firm, because we are stricter, which does not help.* This creates challenges for the auditors, as it is not always clear what can be used as control-information and what not, especially due to the extra standards the Big Four firm has set. P2 explains this challenge: *The boundaries of what is permissible and what is not can shift over time. I believe that as these boundaries shift, there can be uncertainty about what is currently allowed or prohibited. Therefore, there may be some outdated assumptions.* Uncertainties around the output of the data and storage of confidential data need extra navigation through the standards if the auditor wants to stay compliance driven. Furthermore, the uncertainty around what is permissible and what not in terms of AI can shift over time, which creates another uncertainty for auditors that hinders AI adoption. Staying compliant means adhering to all standards, which are uncertain among auditors due to the new and constant evolving nature of AI. The heavy regulated environment creates uncertainties for auditors on the use of AI. This proposes multiple challenges in the adoption of AI for auditors.

4.3.2 External Influence

Stakeholder pressure through clients and regulators presents challenges to auditors when adopting AI. While clients may not be standardized and ready for AI-auditing, there is an expectation for the Big Four firm to be on the forefront of technological innovation. This creates pressure on the auditor to adopt AI quickly. Clients expect added value from the auditor and are interested in what the benefits are that AI can bring into their business. On the other hand, customers view audit services as a cost center. P2 mentions: *When you look at the customers, yes, what the customers expect from us. Well, on one hand, a bit of added value, right? What can you offer us? How can you help us with our strategy in that area? But on the other hand, they also see us just as a cost item, right? Because it's a matter of compliance.* The auditor must balance between using AI that provides extra insights but takes longer due to unstandardized client systems, and the traditional way which may be more efficient. Furthermore, the use of AI gets hindered by the unreadiness internally and at the client. For the use of an RPA such as Datasnipper, client information needs to be standardized. This changes a lot per sector, which poses extra challenges for the auditor. Educational institutions and municipalities seem to be standardized more compared to construction companies for example due to their different opinion on how valuable their data is. SA4 states: *Yes, some clients are further along than others. But that also makes it difficult for the audit industry to implement AI because you are dealing with so many different clients. Each one does it in their own way, and we have to take that into account. So yes, there are a lot of different accounting systems, payroll processing packages, and AI tools need to be specifically adapted to each one, so it's not just one tool that you can use.* Every company is set up differently, which means you can't use AI in a generic sense. To add, clients and auditors often go a long way together resulting in client relationships where AI cannot help with. Clients prefer specific conversations in person instead of online, which results in the AI having less data available to build on. In result, the AI may not recognize the specific situation and have a wrong interpretation about it according to participant M3. Furthermore, external pressures on Environmental, Social and Governance (ESG) issues have an impact on the resource allocation of the firm due to the firm's commitment to sustainability, stakeholder expectations and regulatory requirements. P2 mentions: *That has to do with capacity; we have to make choices about what we focus on. And at the moment, you can't give your attention to everything, so right now we are paying more attention to ESG topics than to AI.* As a result, auditors face several challenges associated with the adoption of AI. Unstandardized clients, increased workload due to additional reporting on ESG and delayed innovation on AI-tools which sets auditors back as AI constantly evolves are the most common ones stated.

5. DISCUSSION

By conducting interviews, this research aimed at answering the following research question:

What challenges do auditors face when adopting AI technologies at Big Four firms?

The following challenges were found to be experienced by auditors when adopting AI-tools: lack of experimentation in a safe space due to the fear of making mistakes in an environment where mistakes can quickly turn into scandals, lack of specific training through practical cases per function of the auditor, difference in perceived complexity resulting in non-optimal cooperation between audit teams, AI being inefficient due to extreme prerequisites within the Big Four, lack of trust due to the fear of using wrong output, the fear of becoming over reliant on AI resulting in becoming less creative and critical, lack of a stimulating environment where auditors feel detached and less committed due to the impersonal structure and size, high workload that results in sticking to traditional methods, heavy regulated and constant evolving standards around AI that create uncertainties, unstandardized clients that create extra challenges due to the need of using multiple tools, client systems that differ per sector, client relationships that are preferred to be in person resulting in the input not covering all aspects and thus being unreliable and external pressure through other important topics as ESG resulting in the firm allocating resources in a way that negatively influences AI adoption.

One of the key challenges identified is the fear of making mistakes, combined with the lack of experimentation in a safe space. While the fear of making mistakes is understandable, due to the consequences, it highlights a culture that may be resistant to change towards AI based auditing. Second, the compliance standards alone influence the efficiency of AI-tools. In the Big Four firm studied, extra compliance standards are applied, which have an even stronger influence on the efficiency. Result of this is auditors sticking to the traditional method because the extreme prerequisites create uncertainty, which influences the adoption of AI.

The challenges faced by auditors vary across sectors due to different opinions on the value of data, resulting in different attitudes towards data and client systems which are not up to date. This pattern is identified multiple times in our research, thus an adaptable approach that considers the diversity of different sectors is necessary.

Looking back at the expectation of the corporate executives that predicted that 30% of corporate audits will be performed by AI in 2025, our research shows that the prediction is unlikely to be true due to the various challenges in AI adoption experienced under auditors.

5.1 Theoretical Implications

Looking back at the literature review of this research, part of the challenges is consistent with those of other studies and suggest the need for them to be addressed. Brynjolfsson (2022) mentioned the risk of potential human bias, incomplete data in the AI output and unclear interpretation of the results leading to difficulties. Our study confirms this due to clients preferring other ways of communication resulting in incomplete data available to generate accurate output. Furthermore, this research agrees with the findings of Eulerich (2021) on the lack of guidance and instructions on the use of IT tools. However, these findings have not described the need for a safe space where experimentation is possible. Our findings show that when general training is provided, the fear of making mistakes predominates due to the lack of tailored examples. As a result, auditors stick to traditional methods of auditing. Literature too mentions that despite the advancements in AI, audit remains labor intensive due the technologies mainly focusing on automating a specific task. This gives the auditor another task, which is to integrate these different systems and applications (Huang & Vasarhelyi, 2019). The findings of this study corroborate this but adds another challenge which is the difference in attitude towards AI in sectors which results in an extra task for the auditor as there is not an adaptable AI-tool available in practice yet.

Not formerly observed challenges relating to the adoption of AI under auditors are, first, the lack of experimentation in a safe space due to the fear of making mistakes in an environment where mistakes can quickly turn into scandals. Second, the challenge of adopting AI in an audit report where cooperation is crucial. This can be traced back to literature on the lack of knowledge (Braun & Davis, 2003). Our research adds the fact of cooperation which increases the difficulty of adopting AI, especially when there is a clear structure such as in a Big Four firm. Third, our findings show the effect of being a 'Big Four' auditor compared with a 'non-Big Four' auditor on the challenges of AI adoption. The increased compliance measures, which are constantly evolving due to the new nature of AI, pose for extra challenges, which need to be considered. In particular, the Big Four auditors find that the need to continuously be aware of the current compliance standards around AI creates a grey area where current AI applications have an uncertain relationship with the current regulatory frameworks.

To conclude, from a theoretical viewpoint, the findings of this study add to a growing body of literature on AI adoption under auditors in a Big Four firm. Due to the study being qualitative, it has addressed the perceptions, attitudes and concerns of auditors related to the adoption of AI, which is valuable for further research. Although part of the challenges can be traced back to existing literature, our research can be seen as reinforcement for these studies in a new, Big Four, research context. This research has therefore contributed to the existing literature on AI adoption in the audit. The findings from this study can be used as input for further research.

5.2 Practical Implications

From a practical viewpoint, the results that emerged from this research give audit firms, specifically Big Four firms, knowledge on the challenges auditors face when adopting new AI-tools in their practice. With this knowledge, firms can take the challenges that were determined in this research into account while implementing the approach for a new or current AI-tool to ensure an effective integration.

First, the lack of education the auditors experience is obvious due to AI's new nature. To overcome this, specific use cases are necessary for auditors to become interested. Auditors have different activities on the daily per function, thus AI use cases should be tailored per function so that auditors can see how the AI-tool would enhance their activities, instead of a general introduction. Next to this, the lack of experimentation asks for a safe space where auditors can learn about the AI-tool while not being scared to make mistakes. Gamification as part of the training could help in this case. Not only would it be a safe place for auditors to experience the AI-tools, but it would also increase the attention AI gets, give instant feedback, foster a sense of collaboration, include real-world scenarios that auditors might encounter and make the change overall easier.

For the organizational challenges, improving collaboration between auditors and IT-auditors would enhance management initiatives by creating a higher sense of attachment and commitment. This could simply start by introducing the AI-tools in a more personalized, active way by creating small, focused teams where auditors can gain hands-on experience with AI-tools. This not only makes the learning process more interactive but also allows auditors to understand the practical applications and gather more perspectives about the use of the tool in their daily work. On the other hand, this would help the IT-auditors by gaining valuable feedback on the functionality and usability. This would help with identifying areas for improvement.

As last, environmental challenges. Different sectors having a different opinion and attitude towards data proposes challenges for the auditors. This indicates that strategies need to be tailored to the specific needs and characteristics of different sectors, as a general approach will be inefficient. To add, auditors should engage in the development of new guidelines that address the specific needs and risks of AI-auditing. Until these specific guidelines are established and clear under auditors, they may also look to the guidelines from other fields that have begun to address AI and adapt these standards into the auditing context. By doing so, auditors can ensure that their practices remain compliant with existing regulations and ethical standards.

6. LIMITATIONS AND FUTURE RESEARCH RECOMMENDATIONS

First limitation is the fact that all 11 interviews were held at the same audit firm (although some worked at different locations), which might lead to bias in the results. This due firm-specific factors and dynamics, which might have impact on the generalizability of the findings. Therefore, future research should aim to include audit departments from multiple Big Four firms in order to mitigate the possible bias and ensure the reliability and generalizability of the research.

In addition, the small sample size, consisting of 11 auditors, may not be completely representative of the whole audit population. A larger sample size is therefore recommended.

Another limitation of this research is that it solely focuses on auditors in the Netherlands. Because of the focus on one country, the research is not fully generalizable to other countries due to possible different conditions under auditors. Future research could expand the scope of the study to more countries to increase the generalizability of the study.

The adoption of AI under auditors is still a subject that has not received a large amount of attention in existing research. Especially related to Big Four firms. There is room for future research on this area, therefore, multiple recommendations are made.

A longitudinal study can be conducted to track the adoption of AI overtime. This would provide valuable insights into how the use of AI evolves within the audit profession, and how effective the firm's strategies are.

In addition, it would be valuable to conduct a study focused on the cost-benefit analysis of implementing AI in audit engagements. This can help firms understand the economic impact and return on investment, which is crucial.

As last, analyzing the adoption of RPA in the audit specifically would help audit firms. This research could examine in more detail how RPA is being used, the challenges it has and the outcomes it achieves. Understanding these factors could help audit firms optimize their use of RPA.

7. CONCLUSION

This research aimed at answering the following research question:

What challenges do auditors face when adopting AI technologies at Big Four firms

Through conducting interviews with experts in the field of auditing at a Big Four firm, the challenges in force that auditors face when adopting AI technologies were identified. Following the identification of these challenges, a data structure was created that provides a clear overview of the challenges due to the categorization under aggregate dimensions linked to the TOE framework. This research provided new insights on the challenges auditors face within Big Four firms and proposes strategies on how to mitigate them. Additionally, it highlights that more future research is needed on AI adoption under auditors. Several recommendations on future research were made which provide audit firms with valuable insights.

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APPENDIX A

Table 1. Complete Interview Sample.

Number	Role	Experience	Age	Education	Interview Duration
SA1	Senior Associate Audit	4 years	(20-29)	Master	40 Min.
SA2	Senior Associate IT-Audit	5 years	(30-39)	[1]RE	28 Min.
SA3	Senior Associate Audit	6 years	(20-29)	Master	28 Min.
SA4	Senior Associate Audit	5 Years	(20-29)	[2]RA	31 Min.
SA5	Senior Associate IT-Audit	6 Years	(20-29)	RE	30 Min.
M1	Manager Audit	11 Years	(30-39)	RA	33 Min.
M2	Manager Audit	8 Years	(30-39)	RA	45 Min.
M3	Manager Audit	7 Years	(30-39)	RA	48 Min.
SM1	Senior Manager Audit	10 Years	(30-39)	RA/RE	25 Min.
P1	Partner Audit	30 Years	(50-59)	RA	28 Min.
P2	Partner Audit	24 Years	(40-49)	RA	27 Min.

[1] RE= Registered EDP-Auditor.
[2] RA= Registered Accountant, equivalent to CPA.

APPENDIX B

Interview guideline

Personal Questions

1. Role and Experience: Could you please describe your current role and your experience in the field of auditing?
2. Age: Would you be comfortable sharing your age group as it might relate to the adoption of new technologies?
3. Academic Background: What is your academic degree, and how has your education prepared you for working with AI in auditing?
4. Experience with AI: Can you discuss any previous experience you have had with AI technologies in your auditing practice?

Technological Questions:

1. AI Tools Usage: What AI tools or resources are currently being used in your firm? How do you use them? What are they used for? How do you interact with these AI tools in your everyday professional life? Could you provide some examples?
2. Technical Challenges: Can you identify any technical challenges or limitations you have encountered while using AI in your audits? Could you provide some examples, perhaps the most recent one?
3. Impact of AI: Does AI technology radically change your way of work or your everyday routine? If yes, how? If not, why?
4. Resistance to AI: What are some reasons why AI tools should not be implemented in your firm?

Organizational Questions:

1. Management Support: How does PWC's management support the implementation of AI technologies? Could you provide examples of specific actions or initiatives?
2. Training: What kind of support and training does your firm provide for auditors to adopt AI technologies?
3. Interactions and Support: How do interactions with your colleagues influence your use of AI technologies in auditing? Are there any challenges in this regard?
4. Organizational Structure and Size: How does the size and structure of PwC influence the adoption and use of AI in auditing? Does it facilitate or hinder the process?

Environmental Questions:

1. Industry Readiness and Barriers: How would you assess the readiness of the auditing industry to embrace AI? Could you discuss specific barriers or challenges that are unique to the audit industry when it comes to adopting AI?
2. Compliance: How do industry regulations and standards impact the adoption and use of AI technologies in your firm?
3. Client Expectations and Needs: How do client expectations shape the way you approach AI in your audit practices? And how are the clients prepared for AI auditing?

General Questions:

1. Considering the various challenges that we've discussed regarding the integration of AI into auditing practices, could you propose specific strategies or measures that might help overcome these obstacles?
2. How could we create a culture of continuous learning and knowledge sharing around AI within our firm?
3. How can management support auditors in acquiring the necessary skills for AI-centric auditing?
4. Conclusion: These were the questions from my interview. As a concluding question, I want to ask if there is anything you would like to mention or explain that you have not yet mentioned?