AI in Auditing: Challenges and Strategies from Big Four Firms

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ABSTRACT

This research examines auditors' conceptions of the relationship between artificial intelligence (AI) performance and explainability in audit decisions. The research draws upon the Technology Acceptance Model (TAM) as its theoretical basis, and explores how perceived usefulness and perceived ease of use influence auditors' intention to use AI. The research is based on five semi-structured interviews with professionals employed by a Big Four public accounting firm. The findings indicate that nearly all auditors characterized explainability as a necessary precondition to usefulness. Auditors accept high performing AI tools only if the outputs are interpretable and defensible. Subsequently, the findings challenge the often ambiguous but accepted notion that there is a trade-off between performance and explainability; we, rather, hypothesize that there is a dependence between performance and explainability. The research extends the existing literature and provably enhances the understanding of TAM in tightly regulated professional settings. Therefore, the research has practical implications for AI tool developers, audit firms and their partners, and regulators to promote responsible adoption of AI.

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Keywords
Artificial Intelligence, Auditing, Explainability, Technology Acceptance Model, Perceived Usefulness, Perceived Ease of Use

During the preparation of this work, the author used ChatGPT in order to refine the text. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

1. INTRODUCTION

In 2016, AlphaGo, an Artificial System (AI) system, beat the world champion of Go, a totally perplexing and ancient game that people thought would take at least a decade longer to solve. Go is significantly more complex and nuanced than chess, and even the best players cannot always explain their moves. What made it most remarkable is not only that a computer system won, but the way it won: with strategies that shocked even the grandmasters, revealing patterns that we, as a species (i.e. humans), had never seen. This event marked the dawn of a new epoch in AI, one in which machines would be superior to humans (although in many cases not very explainable) (Silver et al., 2016).

Artificial Intelligence (AI) was once a futuristic dream that could be seen only in fictions but today it became an essential tool for many industries, including auditing. As AI becomes more common, its potential is realized in variety of sectors, where it enhances efficiency and uncovers data patterns that were previously almost impossible to detect (Lotlikar & Mohs, 2021). In auditing, Artificial Intelligence has proven to be a powerful tool, allowing to automate routine tasks, therefore, improving analytical work of the auditors (Kokina et al., 2025).

However, this technological innovation raises a key issue: high-performance AI systems have powerful analysis capabilities, but they are not transparent to professional audit work (Kindzeka, 2023). This is most clearly illustrated in the contrast between high-performance models (e,g, deep learning, neural networks) versus explainable models (e.g., decision trees, linear regression). The high-performance models can analyze sufficiently massive, complex datasets and find subtle anomalies, thereby, increasing audit quality (Saranya & Subhashini, 2023). Despite this, there are huge challenges for auditors to explain the AI outputs given their black-box nature. Conversely, explainable models provide the auditors with explainable logic that can be traced in terms of decision-making and can be communicated by auditors with the most certainty, but with less accuracy when it is required for exploratory purposes or when non-linearity must be considered if accommodating complex data streams (Assis et al., 2024). The implications of this lack of transparency is a critical issue for audit firms that expect AI systems to be effective but also appeal to regulators and other stakeholders (Lois et al., 2020).

The current study aims to address the issue of how audit firms are countering the challenges of using Artificial Intelligence and devising strategies to make AI systems technologically effective and explainable to regulators and stakeholders. The study will analyze current practices of the Big Four accounting firms in addressing the transparency issues of AI, list the problems of the existing explainability frameworks, which would help these audit firms.

Existing literature indicates that AI can enhance efficiency and accuracy in contract reviews and data analysis (Othman, 2025). There are, however, are limited insights regarding the stumbling blocks of AI adoption, particularly focusing on AI model transparency and explainability (Greenman et al., 2024).

The objective of this thesis is to explore auditors' perceptions of the trade-off between AI performance and explainability in the context of audit decision-making. It aims to understand how auditors evaluate and respond to the strengths and limitations of different AI models, and how these perceptions influence trust, usage, and professional judgment.

Consequently, this study will explore the following research question:

How do auditors understand the relationship between AI performance and explainability, and do they perceive a trade-off in audit decision-making?

This research is academically significant because it transfers a contemporary discussion around explainable artificial intelligence (XAI) into an area of professional auditing that is under-researched. Specifically, the focus of the research is on what auditors considered when thinking about the relationship between AI performance and explainability. It adds to the field of research conceptualisation concerning how people engage with technology through human-technology interaction, paying particular regard to compliance and regulatory disciplines. It also adds to the literature related to trust in automation, transparency, and technology acceptance, but particularly highlights the cognitive and contextual factors shaping auditors' encounters with AI tools. From a practical perspective, the research can be used in developing relevant AI characteristics which will satisfy the auditors' performance expectations, professional obligations, and compliance. Furthermore, the findings can influence audit firms, developers, and regulatory bodies in developing training, guidance, and policy to support the responsible and appropriate deployment of AI technologies in audit procedures.

2. LITERATURE REVIEW

2.1 Use of AI in Audit

Artificial intelligence (AI) application in auditing has recently become a highly discussed topic as a result of firms' attempts to enhance the quality of the audit, as well as the efficiency with which auditors perform the audit, while still detecting risk. Considering that both, big data, along with the increasing complexity of transactions in business, can lead to the worse case scenario of audits being limited by conventional, sample-based approaches (Appelbaum et al., 2017), AI is hailed as a disruptive technology that can possibly revolutionize the audit process.

Many audit procedures today use Artificial Intelligence. AI can, among other things, test journal entries and highlight high-risk transactions which do not follow the typical pattern (Lotlikar & Mohs, 2021). AI can also help with spotting the fraud by learning from all of the cases to spot the pattern. NLP will help auditors find potential misstatements or compliance issues by analysing unstructured data like contracts and minutes from board meetings (Kokina et al., 2025). Audit firms are also using AI in revenue recognition analysis, going concern assessments and even the first draft of audit memos (Odeyemi et al., 2023). The benefits of AI in auditing are well documented. AI enhances audits by processing data faster than humans, and it examines all transactions, not just samples, so it also expands the scope of audits. By reducing the chances that significant fraud or misstatements will be missed, AI may also improve audit quality (Adelakun, 2022). AI also serves as a safeguard against cognitive biases and limitations, as AI will identify patterns or anomalies that humans may overlook

Although a number of recent studies found aspects that promote the use of AI in auditing (Othman, 2025), there is still a significant amount of research on the problems that auditors have, especially dealing with the conflict between explainability and performance of AI, as well as existing research and literature on auditor judgment, analysis, and decision making. While AI is unlikely to replace the position of the auditors anytime soon because of the profession's reliance on human judgement, understanding of the context and professional scepticism, there is a consensus that AI will fundamentally change the concept of auditing and the role of the auditor (Mpofu, 2023).

Lack of the expertise is actually on of the most common problem in this field. Many auditors lack the technical know-how needed to decipher complicated models, which makes them less confident and reluctant to rely on outputs produced by AI (Commerford et al., 2021). The problem of explainability, a crucial auditing requirement where professionals must be able to defend their conclusions and show a thorough comprehension of the evidence underlying their choices, exacerbates this worry. Because of their intrinsic opacity, black-box AI models frequently fall short of this requirement (Crook et al., 2023).

Moreover, regulatory uncertainty related to the usage of AI has complicated the adoption in an already complex environment. Without guidance, auditors may worry about legal liability or being accused of professional misconduct if they rely too much on AI systems that provide faulty or opaque outputs(Odeyemi et al., 2023). Various ethical implications, such as machine learning algorithmic bias, data privacy, and the independence of audits when those audits employ AI provided by third-party vendors, introduce additional risks that remain unresolved. In particular, auditors' perceptions of their trade-off between the performance of AI and the explainability of AI poses one clear gap that this research intends to fill, as it is becoming relevant in the adoption and effective usage of AI in auditing.

2.2 Theoretical Framework

2.2.1 Techology Acceptance Model

The Technology Acceptance Model (TAM) was developed by Davis (1989) and provides a basic model for understanding how individuals accept and use technology. TAM is based on two specific constructs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), that affect peoples attitudes, behavioral intentions and usage. In auditing, TAM has been widely adopted to examine how professionals evaluate the integration of emerging technologies, particularly AI, into their workflows (Jeleskovic et al., 2023).

Perceived Usefulness describes the extent to which a person believes that using a technology will improve the job performance. In terms of auditing, this is demonstrated through Ai tools's ability to increase the efficiency, accuracy, and audit coverage by minimizing human processing of data that previously required a lot of human effort (Bin-Nashwan et al., 2024). AI permits auditors to analyze entire populations of data rather than a sample (Appelbaum et al., 2017; Lotlikar & Mohs, 2021). Coupled with the predictive analysis capabilities of AI, it concludes in a lower probability of anomalies not being detected since the auditor does not rely on sample-tested procedures. Furthermore, Ai also has pattern recognition capabilities, allowing the detection of anomalies, complex relationships within financial information that may be overlooked through traditional analytical methods (Saranya & Subhashini, 2023; Kokina et al., 2025). This technological enhancement affords auditors the opportunity to put their professional judgment and complex reasoning on auditing matters to greater use while routine and repetitive work is completed by technology (AI). The perceived usefulness of AI in auditing is thus directly tied to its ability to enhance task performance and resource allocation, and contribute to enhanced audit quality and assurance reliability (Adelakun, 2022; Kindzeka, 2023).

Perceived Ease of Use is defined as users' beliefs that the usage of a technology will require little cognitive and operational effort (Davis, 1989; Chen et al., 2022). This construct addresses auditors' assessments of how easily AI tools would fit into their current workflow or how easily it can be interactively used, learned, and interpreted. Auditors may be less likely to use AI systems that require extensive training of the auditor, technical knowledge, or logic that may not be readily interpretable, which can lead to additional cognitive load and procedural complexity (Noordin et al., 2022; Jeleskovic et al., 2023).. AI systems that are exceptionally complex, and require a high level of training, technical knowledge or opaque logic to operate may compromise auditors' disposition to adopt new AI tools, in part because they involve additional cognitive load and procedural complexity (Noordin et al., 2022; Jeleskovic et al., 2023). In contrast, AI tools that offer transparent reasoning, tangible output explanations, and fit nicely into the audit process were viewed as easier to use and therefore more acceptable (Lopes et al., 2024; Kokina et al., 2025). Explainability is a significant factor in perceived ease of use, as auditors must not only operate the tool, but also understand and defend its outputs given the regulated and evidence-led nature of their work (Crook et al, 2023; Commerford et al, 2021). Therefore, beyond usability design, ease of use from the user's perspective during auditing is fundamentally a function of the tool's capability to produce outputs that are interpretable, defensible and transparent and that can be aligned with existing professional standards.

Al-Ateeq et al., (2022) applied TAM as a framework in an audit context to investigate ways big data analytics tools impact audit quality by investigating perceived usefulness and ease of use on auditors' decision to adopt these technologies. Noordin et al., (2022) also applied the TAM in their study. They explored the decision-making of auditors from two perspectives: psychological and professional. In this case, PU and PEOU have been identified to predict intentions of auditors to utilize AI-based audit techniques, especially in high-risk areas, which are audit components that are more likely to contain errors, fraud, or complicated estimates; as a result, they call for more thorough testing and solid proof to back up audit conclusions.

While TAM traditionally conceptualizes PEOU as an antecedent to PU (Davis, 1989), some studies suggest that in professional contexts, the relationship may be reciprocal (Noordin et al., 2022). This study adopts this possibility as an open question, explored further through qualitative analysis.

The studies provided evidence of the flexibility of TAM as a research framework, and it was relevant to study auditor attitudes and intentions towards new technologies. The framework of TAM will be used in this thesis in relation to auditors' perceptions of AI performance (related to perceived usefulness) and explainability (related to perceived ease of use). This framework is beneficial to structure the research into how auditors' perceptions of AI impact trust in AI tools and their willingness to adopt these tools..

Based on the literature reviewed and subsequently the Technology Acceptance Model (TAM), this study will present a conceptual framework for researchers to study the way auditors evaluate AI tools around perceived usefulness (performance) and perceived ease of use (explainability). The notion of a perceived trade-off between these two dimensions is introduced as a potential cognitive tension that may shape auditors' reasoning. Instead of assuming that a trade-off exists, this research investigates if auditors face a conflict between performance and explainability in practice. Although actual behavior is not observed, intention to use serves as a conceptual framework for understanding auditors' assessment of the suitability of AI tools for professional use.

The Technology Acceptance Model (TAM) provides a model framework to answer the research question of this study. TAM used AI performance as Perceived Usefulness (PU) and explainability as Perceived Ease of Use (PEOU), which provide a structured framework to examine how auditors assess AI tools in an audit environment. The research question seeks to identify if auditors see a trade-off between PU and PEOU. By using the TAM framework, the study takes the beliefs auditors use when making cognitive assessments and intentions to use AI tools into a coherent and structured way which is widely adopted by other studies. At the theoretical level, the study draws on existing literature while allowing for the exploration of the unique professional, regulatory, and ethical dimensions of auditing practice.

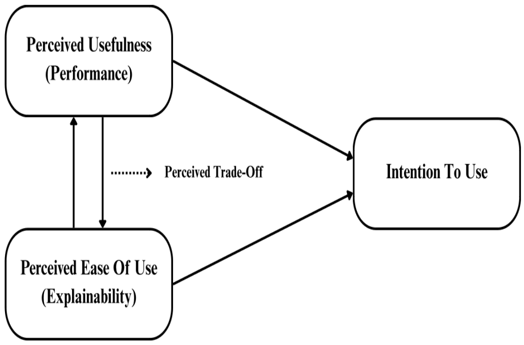

Figure 1. Technology Acceptance Framework

Note. Own work.

3. METHODOLOGY

3.1 Research Design

This study takes a qualitative, exploratory research design to investigate the auditors' perspectives on trading off AI performance and explainability in audit decisions. Considering that auditor's use of AI is a novel topic and current comprehension of how professionals experience the transition to new technology in practice is lacking, a qualitative research design suits the purpose of this study to acquire in-depth, rich context data (Saunders et al., 1996).

This design aligns with the interpretivist research model, which assumes that reality is socially constructed and best accessed through subjective experiences of people (Bryman & Bell, 2015). Since this study examines professionals' sense-making of AI tools in the context of their job constraints, standards, and accountability, it requires a methodology that accesses meanings, judgments, and beliefs rather than quantifiable relationships. An exploratory strategy is appropriate for this study since it enables exploration of comparatively uncharted problems for which theoretical frameworks are still being formulated and for which empirical evidence is scarce. Exploratory research, Saunders et al., (1996) asserts, is particularly valuable when the objective is to clarify understanding of a complex issue, uncover hidden dynamics, or yield fresh information that can inform future theory development.

3.2 Sampling

Purposive sampling was used in this study to choose participants who were directly related to the goal of the investigation, which was to find out how auditors view the connection between explainability and AI performance in audit. Purposive sampling was suitable for obtaining experience-based insights from experts acquainted with AI tools, given the exploratory character of the subject and the growing importance of AI in auditing (Guest et al., 2013).

More precisely, auditors from one of the Big Four accounting firms, which are renowned for their early adoption of cutting-edge technology like artificial intelligence, were recruited using expert purposive sampling (Issa et al., 2016). Additionally, participants were selected according to preset standards for professional background and exposure to AI in auditing, as shown in Table 1.

Although the sampling method limits how generalizable the results are to other contexts, through purposive sampling, it makes the data more valuable and credible by limiting exposure to auditors most likely to encounter performance–explainability challenges in practice (Palinkas et al., 2015). A total of five auditors were interviewed, all of whom were quite experienced, in some capacity, with AI tools.

Table 1. Criteria for selecting interview participants

Criteria
1. At least 3 years of experience in auditing in Big Four firms.
2. Demonstrable familiarity with AI tools used in or around audit engagements

3.2 Data Collection

In order to explore how auditors understand AI performance and explainability in audit decision making, semi-structured interviews were the only method of data collection used in this study. Semi-structured interviews are appropriate for qualitative, exploratory research that aims to obtain deep understandings of unique experiences, interpretations and rationales in an under-explored area (Adams, 2015). A semi-structured interview are flexible enough to capture unexpected perspectives but still allows the researcher to canvass relevant topics. Using semi-structured interviews is aligned with an interpretivist paradigm which seeks to explain how humans develop meanings in a dynamic technological setting like auditing (Ruslin et al., 2022).

The interview guide was developed from academic and applied perspectives. The academic underpinning was the Technology Acceptance Model (TAM) reflecting perceived usefulness and perceived ease of accessibility. The thematic structure of the guide was designed to allow discussions to flow as naturally as possible. These themes included the participant's professional background, their AI experience, the potential benefits and limitations of AI tools, and AI readiness at organization. The discussions also paid particular attention to the possible tensions in performance versus explainability, which is a primary issue in the current literature around AI and auditing (Raisch & Krakowski, 2021).

Interviews were recorded with permission using Microsoft Teams, and transcriptions of the conversations were made. The accuracy of the transcripts was checked, and any unnecessary words were removed to make them more readable. Each participant was given a unique identification number (Participant 1 through Participant 5) to maintain confidentiality. This identification was used throughout the findings to attribute insights without revealing organisational or personal information.

3.3 Data Analysis

Next in the research process was to analyze the data collected through the transcribed interviews employing the Gioia Method (Gioia et al., 2013). This method presents a consistent and transparent process for qualitative data analysis and is ideal for inductive, exploratory research. This method provides a place for researcher interpretation, rather than simply reporting descriptive and conceptual analysis. It also enables researchers to develop grounded theory. The method of analysis is closely tied to the language and lived experience of the participants.

The analysis contained three parts, in the standard order of the Gioia methodology. The first-order analysis focused on the key expressions and terminology used by participants which were precisely extracted and categorized as first-order concepts. Because these concepts stayed close to the informants' own wording, the researchers could ensure that they captured the participants' perspectives as closely as without losing any of their lived experience.

The second-order analysis followed the same process as explained previously, in that the first-order concepts were interpreted and grouped into more general second-order themes. These second-order themes were guided by the theoretical lens of the Technology Acceptance Model (TAM) and the study's purpose considering the perceived trade-off between the performance of AI and the perceived explainability of AI. In a nutshell, this stage required a shift from descriptive coding to a more analytical-theoretical interpretation of the data. At this stage the researcher started to look for patterns across interviews and attempt to connect, or link, to conceptual (theoretical) constructs such as perceived usefulness and ease of use, trust and transparency.

At the last stage, the second-order themes were then synthesized to develop aggregate dimensions representing the highest level of abstraction in the data structure. The aggregate dimensions articulated how auditors reframe their appreciation of the value and limitations of AI tools, the role that explainability plays in the creation of trust and professional accountability, and the organizational and technological conditions surrounding audit decision-making and how AI is seen as either support or impediment.

Appendix B specifies the full data structure, which also contains representative quotes for all first-order concepts. Following this structure the findings will be presented in the following chapter.

4. RESULTS

In order to investigate auditors' perceptions in relation to the application of AI in audit practice, five semi-structured interviews were held with professional auditors from Big Four firms. The findings are organized using the Technology Acceptance Model (TAM) and were analyzed using the Gioia method. Thus, a data structure was created working from first-order concepts to identify five distinct second-order themes, combined into two aggregate dimensions: Perceived Usefulness and Perceived Ease of Use. The data structure provides a straightforward summary of how auditors evaluate AI tools in terms of practical benefits that help them and useability limitations. Each of the themes will be discussed in this chapter.

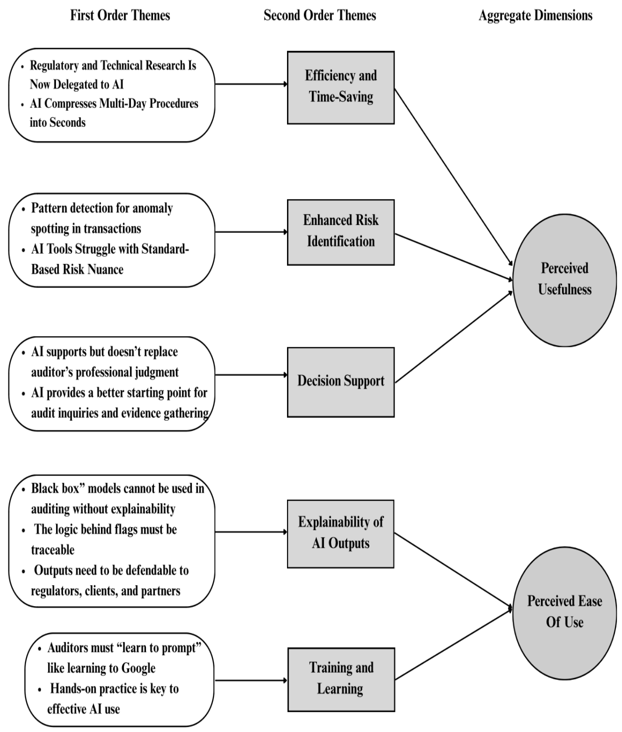

Figure 2. Data Structure

Note. Own Work.

4.1 Perceived Usefulness

The relation of the insights generated from first-order themes is first addressed the Perceived Usefulness dimension of the Technology Acceptance Model (TAM), which describes the extent to which auditors perceive AI tools to improve their performance and effectiveness when performing audit tasks. There were three second-order subthemes identified under this dimension based on the themed coding: Efficiency and Time Savings, Improved Risk Identification and Decision Support.

Perceived Usefulness, as a higher-order theme, considers how AI tools assist auditors in their work by facilitating the automation of audit tasks as routine tasks, improving audit risk identification, and more effectively providing analytical input to facilitate their decision making. The subsequent sections discusses each of these themes in detail.

4.1.1 Efficiency and Time-Saving

AI always appeared useful to auditors in terms of the time it saves in operational and repetitive tasks, but this perceived usefulness was affected by context. Participants did not describe AI to be a universal time-saving technology, but made place emphasis of AI's role in making routine tasks quicker.

The most clearer improvements were made with reconciliation and for internal consistency procedures. Participant 4 noted a task that used to take a maximum of 6 hours now takes under a minute. This suggests that AI's usefulness is closely related to the predictability and clarity of the task.

What became analytically prominent in the responses was that time saving was not only about pace, it was about allocating resources under pressure and deadlines. Auditors often work under deadlines which are rigid, particularly during busy audit period. AI was valued not because it eliminated work, but allowed auditors control again over their timetable. Similarly to Participant 1' s response, AI did not change the quality threshold expected from auditors, it just allowed auditors more space to meet it.

Importantly participants did not equate speed with trust. Most participants framed AI-generated results as comparable to the findings of an assistant, but still emphasized that AI-generated results have to be validated by audit staff manually, even AI-generated spreadsheet manipulations. Some participants emphasized that the verification process, in some way diminished the time savings of using AI. This is consistent with the understanding that usefulness is relative. AI tools could accomplish a task in few seconds, but if auditors were not comfortable with the trust of the produced result, they see less value in the outcome produced by the tool.

4.1.2 Enhanced Risk Identification

Another way auditors found AI useful was in supporting the early identification of audit risks as it relates to detection of patterns in the data or flags anomalies. This theme captures how participants conceptualized AI as a tool to enhance awareness of areas to focus their attention, particularly during the planning and scoping stage of their audit process.

A number of participants described AI as a useful initial filter to identify patterns or inconsistencies that they otherwise would not have detected through a manual level of review. Participant 5 stated, *"AI-based tools can sift through thousands of transactions and identify relevant ones that do not fit an expected pattern. It helps to get our attention more quickly on the higher risk areas instead of manually sampling at random."* AI does not remove or absolve the risk judgment process for the auditor but can encourage auditors to focus on potentially material areas sooner.

This theme confirms that auditors conceptualize AI performance as targeted risk identification, rather than general predictive success. Within pushback against AI, auditors did not see AI as intelligent in a human sense, but rather something that was functionally useful, if confusion avoided, utilizing large datasets to identify instances that worthy deeper human investigation. In this sense, auditors agree AI is a diagnostic assistant, useful in filtering the areas of attention but not adequate for drawing its own conclusion.

However, a number of the participants elaborated on these benefits. They explained that AI is valuable when risks are quantitatively and behaviorally based but not standard-based or contextual. Participant 2 explained, "These tools view every problem as general, but do not think that it might be standard-based." This provides an indication of a restriction: AI assists in finding anomalies, but it does not help interpret anomalies in the normative world of auditing standards, where professional judgement is central.

4.1.3 Decision Making

Auditors viewed AI's ability to support decision-making, rather than replace decision-making, as the third way AI came to be considered useful. Participants in the interviews repeatedly noted that AI tools were valuable in structuring their approach and speeding their cognitive processes, however, they stated that their final professional judgments will ultimately be their own. For example, participant 3 described AI as "a point to start from," noting how AI was beneficial in unfamiliar topics or standards. This suggests that auditors were using AI to support their decision-making, instead of replacing it. AI supported their decision making by forming hypotheses, identifying priority audit procedures, and kick starting their reasons for review but evaluating risk, materiality, and sufficiency evidence is still manual.

With respect to the research question, this theme indicates that auditors do not anticipate AI to execute judgment but rather to develop their own judgment capabilities more quickly and confidently. Auditors perceived AI to be most useful as a decision scaffold, as a supportive mechanism that enables audit thinking, speeds up planning, and can structure complex tasks. The value of AI to the audit process is not in providing the auditor with answers and replacing the auditor's expertise, but enabling the auditor's expertise to be used more efficiently within the time and resource constraints of modern audit engagements.

4.2 Perceived Ease of Use

As defined in the Technology Acceptance Model, Perceived Ease of Use (PEOU) refers to the extent to which auditors find AI tools intelligible, intuitive and manageable in practice. In this study ease of use was newly strongly related to auditors' ability to interpret AI outputs and being confident in using the AI tool with no excessive effort and without extensive training. Two second-order themes manifested under this dimension: Explainability of AI Outputs and Training and Learning. Each of these is described in detail below.

4.2.1 Explainability of AI Outputs

Auditors continuously voiced that AI tools are only usable if the final outputs are clear, interpretable, and usable in a professionally meaningful way. Participants did not determine ease of use based solely on user interface, but rather on the amount of mental effort to understand and use the AI-generated results in accordance to audit standards.

Participant 5 elaborated, *"A lot of the time, the tool will flag something as suspicious, but it does not tell you why. Without that clarity, it is much harder to be able to use those results to satisfy part of an audit's documentation standards."* In other words, the lack of transparency means that auditors have to do more work in interpreting the issue, undermining the efficient design of the tool.

Auditors and other participants stressed that results must be traceable and defensible. As Participant 1 stated, *"It should always be re-performable. If we can't see how the AI got there, how can it be used as evidence?"* This is important because results that lack explainability are not only more difficult to trust, but are often unusable document and weak evidence in formal audit files.

As determined by the Technology Acceptance Model, the findings also indicate that auditors are less apt to adopt AI when the outputs are non-transparent. Even tools that are highly performing are viewed as burdensome if they cause higher cognitive effort. In audit situations, explainability is not simply a preference, but is an expectation.

4.2.2 Training and Learning

The second significant factor influencing perceived ease of use was the auditors' ability to use AI tools confidently. Throughout the interviews, participants characterized learning as potentially straight forward, but constrained by a lack of hands-on training and direction. Most had access to general webinars, or self-guided materials, but found them lacking in terms of developing a fuller understanding.

Participant 2 stressed the importance of using real audit scenarios in training, stating, "Full-scale AI development still has a far way to go for hands-on training and practical exposure." There is a gap between awareness and operational ease; the auditors knew they were able to use AI, but they felt constrained by the absence of structured learning experiences specific to auditing. In its absence, AI tools were used in a way that was fractured based on the team's uniqueness and goals.

Participants also mentioned that usability is much easier when AI is presented as an evolution of a skill they use regularly, rather than a technology barrier. Participant 1 specifically compared it to digital tools they use every day: "We all had to learn how to Google. Now you have to learn how to use this technology. It is not anything different than that." This response is a good indication that auditors are willing to learn when the framing and support is appropriate, but ultimately they need training that fits with how they think and work.

The findings have important implications for the Technology Acceptance Model. These findings indicate that ease of use is determined not only by the design of the tool, but also by the organizational infrastructure surrounding learning. If auditors do not have structured, scenario-based training related to auditing practices, then they are more likely to see the use of AI tools as effortful or risky. As mentioned, training is a key part of forming adoption - especially when paired with an audit standard that emphasises accuracy and accountability.

5. DISCUSSION

This chapter examines these findings while considering the research question and theoretical framework that underpin the study. Using the Technology Acceptance Model (TAM) as a basis for examining and interpreting the results, this chapter considers how auditors views on the adoption of AI in audit work are influenced by perceived usefulness (PU) of AI and perceived ease of use (PEOU) of AI. The analysis accounts for the perceived implications of the relationship between AI performance and its explainability and, therefore, considers whether or not auditors perceived these dimensions to be complementary or conflicting.

5.1 Interpretation of Results

5.1.1 Perceived Usefulness and Perceived Ease of Use

The overall findings of this study support the key constructs associated with the Technology Acceptance Model (TAM) and contributed a more nuanced interpretation regarding how perceived usefulness (PU) and perceived ease of use (PEOU) are experienced in the auditing profession. Participants did not view the two constructs as separate constructs or bi-directionally mutually reinforcing. Rather, participants highlighted that explainability, as part of PEOU, is a condition for usefulness recognition.

Auditors reported usefulness primarily in AI's ability to decrease time on audit components that are operational, repetitive tasks (i.e., account reconciliations, documentation preparation, and IFRS searching). These findings align with Bin-Nashwan et al. (2024), who reported that auditors adopt AI tools that more- or less-efficiently accomplish a task or aid users in generating better financial analytic knowledge. While AI was found to be useful on a surface level, this use was highly task contingent; that is, AI was useful with audit components that were structured and low-risk, and usefulness in audit components that required professional judgment disappeared completely. This conclusion could also be supported with Al-Ateeq et al. (2022), who found that usefulness is often conditional based on the structure and standardization of a task.

Ease of use was most strongly impacted by whether or not AI outputs were explainable. If a tool produced a result that auditors could not trace, understand and justify in their documentation, the tool was quickly deemed difficult to use, regardless of ease of interface or operational functionality. This aligns with Chen, et al. (2022) and Lopes et al. (2024), who state that cognitive transparency, and traceability are both essential cognitive inputs with respect to attain cognitive understanding and ease of use in professional situations. For auditors, explanation is a requirement, not a preference, because of professional accountability and regulations.

Importantly, the findings indicate that auditors did not perceive PU and PEOU as mutually supportive equally. While TAM has commonly presented PEOU as contributing positively to PU (Davis, 1989), this research found that in audit practice PEOU, especially explainability, has to exist prior to acknowledging usefulness. Auditors rejected the tool outright based on the lack of explainability, even if there would have been potential performance improvement. Tools that were interpretable and justifiable were more likely to be regarded as useful and trustworthy. This is consistent with Noordin et al. (2022) in that auditors' perceptions of usefulness and technology are strongly sculpted by how clearly the logic of the technology overlapped with their professional expectations.

In conclusion, auditors perceived explainability as a precondition, not a supplement, to usefulness. Even though TAM suggests that ease of use is facilitating perceived usefulness, the study demonstrated that in auditing, explainability must come first. Auditors assessed AI tools mainly on the basis of whether the outputs could be understood, justified, and defended; once this condition was satisfied, they then considered potential performance benefits of the tool. This highlights that in the audit context, explainability is not simply a precursor to perceived usefulness but rather it is the lens through which usefulness is recognized in the first place.

5.1.2 Perceived Trade-off Between Performance and Explainability

This paper investigated whether auditors see a trade-off between AI performance and explainability when making audit decisions. The results indicate that a majority of auditors did not accept such a trade-off in practice. Most auditors dismissed tools that provided strong performance but lacked explainability for a professional obligation, not a preference; software that could not be justified or traced was viewed as unusable regardless of its technical capabilities.

Although this relationship was not examined in the previously reviewed literature, Saranya and Subhashini (2023) describe a broader debate between AI developers between high-performing black-box models and explainable systems. However, the auditors for the majority of this study did not see performance and explainability as qualities that could be weighed against each other; rather the auditors saw explainability as enabling performance. This can be characterized as consistent with other research regarding the auditing and accounting field that has drawn attention to the aspects of traceability, defensibility, and cognitive accessibility as pre-requisites for any adoption of AI (Chen et al, 2022; Lopes et al, 2024).

5.1.3 Intention to Use

As proposed in the TAM framework, a technology's intention to be used is influenced by its perceived usefulness and ease of use (Davis, 1989). In the current study, most auditors described an intention to adopt AI tools, although this intention was predicated by conditions. Auditors' willingness to adopt AI was based less on its efficiency or novelty and more about achieving professional expectations related to transparency, traceability, and accountability. Auditors reported they were more likely to adopt AI when a tool was explainable and provided concrete value in a task. Conversely, auditors were less likely to adopt AI when the tool produced outputs that required interpretation and exploration in context to use. These findings are similar to those of Noordin et al. (2022) who find that AI adoption is underpinned by professional considerations in addition to psychological considerations. In summary, auditors' intention to use AI is situational and dependent on judgment about how the tools meet cognitive and regulatory definition.

5.2 Theoretical Implications

The objective of this research was to investigate how auditors conceptualize the link between AI performance and explainability in their audit-based decision making. Although the study employed Technology Acceptance Model (TAM) as a framework for better understanding how perceived usefulness (PU) and perceived ease of use (PEOU) shaped auditor evaluation of AI technology, few auditors described explainability, a key component of PEOU, as a factor of supporting usefulness. Most auditors described explainability as a precondition to recognizing usefulness. This refines existing theoretical assumptions and underscores that technology acceptance in a professional context is impacted by regulatory, cognitive, and ethical conditions.

Changes in beliefs must be understood within the context of the literature that focuses on the supposed trade-off between performance and explainability in the AI literature. While earlier models suggested that in order to obtain more advanced performance you have to give up the ability to explain, the study found that auditors do not accept this trade-off. This insight not only calls into question some common acceptance assumptions, but suggests that established acceptance models may need to be sensibly revised when applied in regulated industries. The results were aligned with previous studies by Chen et al. (2022) and Lopes et al. (2024) but extended their findings by suggesting explainability needs to more explicitly monitor to models of technology adoption in audit and like fields.

Finally, this thesis also demonstrates how TAM can be applied to study the adoption of AI tools in complex professional contexts. By studying TAM in an environment with legal accountability and human judgement, the research not only demonstrates TAM's adaptability but highlights its limits as well. The research engages future researchers to extend TAM with different constructs, such as explainability, trust, or perceived risk, to understand professional decision-making.

5.3 Practical Implications

The results of this research provide a number of actionable implications for audit firms and technology developers who are looking to develop AI tools for use in professional audit contexts. First, the results show that explainability must be a central feature of tool design. Even high-performing AI systems will be under-used when auditors cannot understand, rationalize, or document their outputs. As a result, developers should invest in features which support transparency, like user-facing explanations and traceable logic paths.

Second, this study emphasizes the need for tailored training programs. While auditors indicated the need for practical, scenario-based hands-on learning beyond introductory AI, they are less likely to integrate an AI tool into their practice as firms that have a safe onboarding process or structured, procedural approach, and continuous learning are more likely to be on ramped up for adoption. Finally, regulators and standard setters, should consider the implications of the study in the role of explainability in audit quality and, guidance to support the responsible use of AI in assurance services.

6. LIMITATIONS

While this research offers valuable insights into how auditors understand the relationship between AI performance and explainability, many limitations should be recognized. First, the study only included five people from only one firm, which limits the generalizability of the findings. While this research had a qualitative design focused on depth rather than breadth, future studies using a larger sample of auditors from a variety of groups, firms, regions, and roles would benefit from a broader understanding of perceptions.

Second, the research only examined perceptions, not actual behavior. While the Technology Acceptance Model (TAM) allows for intentions to use to represent use, future studies may wish to combine these types of studies with observational or behavioral data to examine how auditors actually engage with AI tools in practice. Finally, this study focused only on explainability and performance, but future studies may examine other adjacent factors such as perceived risk, trust in automation, or other organizational supports.

Ultimately, the context of the study is identical to the audit profession where regulatory and documentation standards are stringent. Future research may explore inquiry about similar patterns to the audit domain in other professional settings such as healthcare, legal, or financial advisory, where accountability is clearly paramount. Assessing the theoretical model of providing explanation as a core construct may be able to strengthen prediction in other high stakes decision-making settings.

7. CONCLUSION

This research aimed at answering the following research question:

How do auditors understand the relationship between AI performance and explainability, and do they perceive a trade-off in audit decision-making?

The study used the Technology Acceptance Model (TAM) as a theoretical framework to understand how perceived usefulness (PU) and perceived ease of use (PEOU) influence auditors' assessments of AI tools, and whether performance and explainability are viewed as competing or complementary. Also, the results indicate that most auditors do not see a trade-off. There was instead a view of explainability, particularly as a way to interpret and justify AI outputs, as necessary for acknowledging usefulness. Tools that lack transparency are not seen as useful even if the technical strength of the tools is high. This suggests a more sequential relationship in TAM, where it seems the auditors must regard ease of use before usefulness can be acknowledged. In addition to addressing ease of use and user evaluation of AI tools, auditors' intention to use AI was also conditional based on fit-for-purpose to the standards of the audit, reasoned professional judgment, and documentation.

Additionally, this study contributes to theory by refining TAM in the context of regulated professions, and by contesting a prevailing assumption in AI research that performance and explainability are inversely correlated. Practically, it reminds audit firms and developers that explainable AI design and training should be prioritized. The current study, although limited by sample size, can serve as the groundwork for future research into AI adoption in other high-accountability professions.

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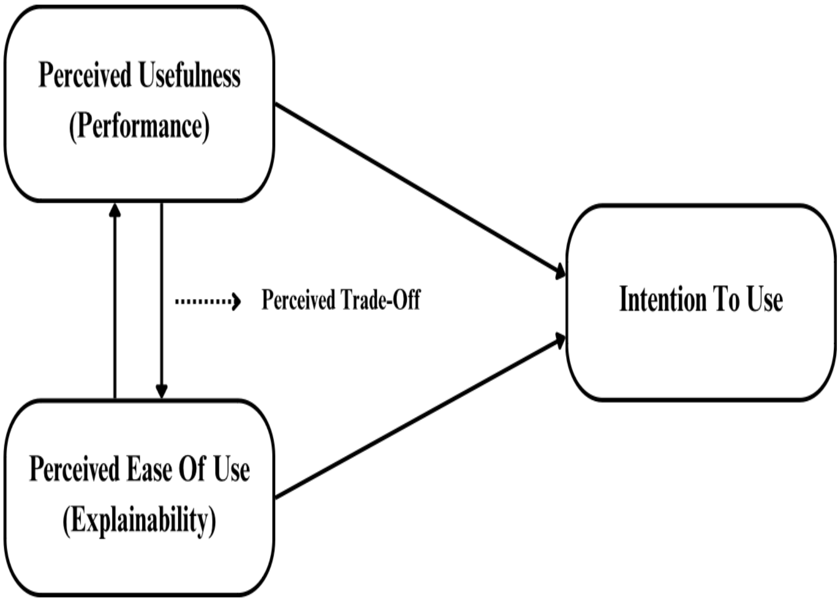
APPENDIX A

Figure 1. Technology Acceptance Model (TAM) Framework for AI Adoption in Auditing



APPENDIX B

Exemplary Quotes from Interview Participants

Quotes	First Theme Order	Second Theme Order	Aggregate Dimension
Participant 1: *"I sometimes use AI to rationalize, you know, IFRS accounting, because I just do not want to read too much into it. So then I use it as kind of the initial search.cEspecially I used a lot of the time for things which are not directly to do all the work I think, but it's more around it, right? Initially we were searching in IFRS books to find the right and the relevant paragraphs. And now you could use this technology to answer your questions and it helps you a lot with the initial search through these kinds of regulations. So that is essentially a very happy addition to the job to not have to be a librarian."*	1a)Regulatory and Technical Research Is Now Delegated to AI	Efficiency and Time Saving	Perceived Usefulness
Participant 4: *"It was about five to six hours working and now it is just 5–6 seconds. Then you will get actually the data and reconciliation procedures within no time done."*	1b) AI Compresses Multi-Day Procedures into Seconds	Efficiency and Time Saving	Perceived Usefulness
Participant 2: *"In my opinion, AI improves audit quality by enabling faster data processing and helping identify anomalies across large data sets, it reduce manual efforts in routine tasks, which we have a lot like 3 testing allowing audit to focus more on judgmental base procedures and resassessment."* **Participant 5:** *"AI contributes to audit quality by making our work more focused and data-driven. For example, during substantive procedures, AI-based tools can sift through thousands of transactions and isolate those that deviate from expected patterns. That allows us to direct our attention to higher-risk*	2a) Pattern detection for anomaly spotting in transactions	Enhanced Risk identification	Perceived Usefulness

areas rather than manually sampling at random."			
Participant 2: *"When you input the data from our audit procedures to gain certain explanation, it can be misrepresented by AI since these tools consider every problem to be general, but and does not consider that it may be more standard-based."*	2b) AI Tools Struggle with Standard-Based Risk Nuance	Enhanced Risk identification	Perceived Usefulness
Participant 4: *"Because one of the other tools we use is also the reconciliation of the financial statement and the internal consistency within the financial statement itself. But I repeat, we always have to check if everything is correct. Or if the tool took the data correctly from the documents we provide. You have always to use your professional critical attitude as an auditor to check the data you get from the AI."*	3a) AI supports but doesn't replace auditor's professional judgment	Decision Support	Perceived Usefulness
Participant 3: *"In supporting, sometimes, like I said, when I run into some issues with regards to regulations or some rules or laws, it's just easy to search up and then have more background on a certain topic before I make my own decisions. Because I don't take decisions based on what AI says. It's more like support for understanding what the issue is, if it is an issue, how big of an issue is it. It is more of a supporting evidence or supporting information, but it's also not the key information. I use it to support and then I do more research and then I come to a conclusion. It is like more of a point to start from."*	3b) AI provides a better starting point for audit inquiries and evidence gathering	Decision Support	Perceived Usefulness
Participant 1: *"If AI cannot explain what they do, I will never put reliance to it. I had clients which asked us to provide assurance over forecasting models, and then the reasoning is: we know that the forecasting model works under a certain set of*	4a) "Black box" models cannot be used in auditing without explainability	Explainability of AI Outputs	Perceived Ease of Use

parameters. So what happens if you're outside of those parameters? Then there is no assurance anymore on how the model behaves. It should always be re-performable. It can help with a step, but from the outside you always need to be able to quickly validate if that makes sense or not. So it is never a full black box out there. Sometimes they portray it that way that is not how it works. If it is such a black-box thing we cannot explain, how can you use it as audit evidence?" **Participant 5:** *"Often, the tool will flag something as 'suspicious,' but there's no explanation of why it was flagged. That lack of clarity makes it harder to use those results in a way that satisfies audit documentation standards. I sometimes feel like I am translating the AI's 'opinion' into something the audit file can actually defend."*			
Participant 4: *"Well, just like I mentioned, like when you want to scan for instance data, what you get from the client that is a very fast way to get your data within, for instance, Excel or something like that. But I repeat, we always have to check if everything is correct or if the tool took the data correctly from the documents we provide. You have to use your critical attitude as an auditor to check the data you get from the AI."*	4b) The logic behind flags must be traceable	Explainability of AI Outputs	Perceived Ease of Use
Participant 5: *" Explaining outputs to colleagues is usually easier because we have similar training and understand the limitations of these tools. But with clients or partners especially those who are skeptical of new tech it is more challenging. You cannot just say, 'The system flagged it. You need to translate that flag into something meaningful and supportable, and without understanding how the AI works, that's tough. I have*	4c) Outputs need to be defendable to regulators, clients, and partners	Explainability of AI Outputs	Perceived Ease of Use

had moments where I had to do extra legwork just to validate what the AI suggested because I did not want to rely blindly on something I could not explain.” **Participant 2:** *“ If a tool provides insights that cannot be explained, it weakens our ability to form an audit opinion and can create issues. Like some regulators and stakeholders, they expect clarity and auditability more than efficiency or some powerful processes.”*			
Participant 1: *“ When people talk about trainings, it is like: how did we learn how to Google, right? So if we talk about AI nowadays, it is a lot about GenAI. We all need to learn how to Google. And now you need to learn how to use this technology. Do not take it as anything more difficult than that. Of course, you can use longer statements within Google because they are more effective which we now call prompts and we can do some prompt engineering. But besides that, it's kind of the same as learning any application or learning how to search in Google.”*	5a) Auditors must “learn to prompt” like learning to Google	Training and Learning	Perceived Ease of Use
Participant 2: “*Our company has started providing training sessions and e-learning modules related to AI and data analytics, especially through special training and our internal tools. However, full-scale AI development still requires more hands-on training and practical exposure.”*	5b) Hands-on practice is key to effective AI use	Training and Learning	Perceived Ease of Use

APPENDIX C

Interview Overview

Participant Number	Organization	Function	Duration	Age (in years)	Experience in Auditing (in years)
P1	EY	Senior Manager	22 minutes	34	10
P2	KPMG	Audit Supervisor	10 minutes	27	3
P3	EY	Senior Auditor	15 minutes	28	4
P4	EY	Senior Staff	13 minutes	33	4
P5	KPMG	Senior Auditor	12 minutes	26	4

APPENDIX D
Interview Guideline

Section 1: Personal and Professional Background

1. **Role and Experience**
   Can you describe your current role and your experience in the auditing profession?
2. **AI Exposure**
   Have you worked with AI tools in your audits? If so, what kinds of tools and how often?
3. **Age group**
   Would you be comfortable sharing your age?

Section 2: Perceived Usefulness (AI Performance)

4. **Value and Impact**
   In your view, how does AI improve audit quality, accuracy, or efficiency?
5. **Reliance on AI**
   In your current audit work, does AI play any role in supporting or influencing your decisions? If not, why?

Section 3: Perceived Ease of Use (Explainability)

6. **Transparency**
   In your experience, when AI tools are used in audit work, how clear or unclear are their outputs?
7. **Communication with Others**
   Have you ever needed to explain or discuss outputs from an AI tool with colleagues, clients, or regulators? If so, how did that go?
8. **Importance of Explainability**
   From your perspective, how important is it that AI tools are explainable or transparent?

Section 4: Trade-off Between Performance and Explainability

9. **Tension Between the Two**
   Do you think there can be a trade-off between how well an AI tool performs and how easy it is to understand?
10. **Your Preference**
    Would you prefer a highly accurate AI tool that is hard to understand, or a more transparent one that's less powerful? Why?

Section 5: Organizational and Industry Context

11. **Firm Support**
    What kind of support or training does the company offer for using AI tools?
12. **Industry Readiness**
    How well do you think the audit profession is handling the growing use of AI?

Section 6: Final Reflections

13. **Improvements Needed**
    What kinds of improvements could help make AI more useful and responsible in audit work?
14. **Final Thoughts**
    Is there anything else you'd like to share about your experience with AI in auditing?