AI Use in Auditing – A Technology Dominance Perspective

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Abstract

AI technologies' use in audit work is expected to deliver cost efficiencies and improve decision-making. However, some deleterious effects of reliance on technology are discussed in the literature. Using the effects of technology dominance on audit work, enunciated in the theory of technology dominance (TTD) as theoretical anchor and qualitative methodology, our study investigates the consequential effects such as deskilling, automation bias, complacency, and illusion of competence on audit work and how audit firms deal with those effects. Our study observed that audit firms are prepared to deal with these risks through controlled deployment and use of AI tools, visibility of the tool, upskilling of early career auditors, and matching the tool with the auditor's skills. Balancing the automation of task with the retention of expertise; sharing of data, models and economic benefits with the audit clients; and loss of interest and therefore the expertise to do mundane tasks are challenges observed.

Keywords: Auditing, Artificial Intelligence, Technology dominance

1. Introduction

Discussions surrounding the use of artificial intelligence (AI) technologies in auditing highlight potential cost efficiencies, improved audit decision-making and quality, disruption, and risks to the profession. AI enabled tools stand out from previous auditing technologies due to their ability to automate cognitive tasks, to change the trade-off between the speed, cost and quality of auditing (Almufadda and Almezeini, 2022), their capacity to simultaneously help mine the three dimensions of information in auditing – space, time and internal structure (Gao and Han, 2021), and their ability to exercise intentionality in the development of algorithms, protocols and action selection (Murray et al., 2021). They have the potential to link often widely dispersed actors and opening-up data rich domains to support systematic decision-making that were previously beyond reach due to cognitive limitations (Lehner et al., 2022).

Recognizing its potential value big-4 audit firms have invested $ billions in AI (KPMG 2024). According to an estimate by the World Economic Forum, AI is expected to perform more than 30% of corporate audits by the year 2025 (WEF, 2015). With such massive investment in AI by the audit firms and their clients, AI use is expected to support auditors' decision-making (KPMG, 2024) and create new opportunities and risks in the auditing profession (Dyball and Seethamraju, 2022; Janssen et al.,2020; Kend and Nguyen, 2020).

Though AI technologies are expected to offer cost efficiencies and support decision-making, auditors' reliance on such technologies, it is argued, may lead to poorer decision-making, inattentive expert decision makers, and deskilled knowledge workers (Sutton et al., 2023) with their usefulness limited by the capabilities of human users (Koreff et al., 2023). Unlike other technologies that were used to automate manual tasks, AI would automate cognitive tasks in the auditors' decision making process, and with increased dependence, there is a risk of auditors abdicating their responsibility for judgment (Munoko et al., (2020). Such reliance on AI technologies may result in deskilling of auditors (Triki and Weisner, 2014), foster complacency (Rinta-Kahila et al., 2023; Parasuraman and Manzey, 2010), amplify bias (Tillbury and Flowerday, 2024) and create an illusion of competency (Fischer, 2015) in their decision-making. With their use likely to become mandatory and widespread in audit firms supporting auditors' decision-making (Dowling et al., 2018), future AI enabled tools are promising to extend this further and mimic auditor judgment.

It is therefore necessary to examine and understand how AI technologies impact audit decision-making within a broader context where environmental factors, systems and user interactions play a significant role (Sutton et al., 2023). Several scholars called for studies to understand and codify this human-AI interaction and the effects of the AI

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dominance in audit (Samiolo et al., 2023; Sutton et al., 2023; Murray et al., 2021; Koreff et al., 2023; Vitali and Giuliani, 2024).

Therefore, our overarching research question is "how does the use of AI tools impact auditors' decision-making? As the focus is to understand the dominant effect of AI use, we use theory of technology dominance (TTD) (Arnold and Sutton, 1998; Sutton et al., 2023) and the potential effects – deskilling, automation bias, complacency, and loss/illusion of competence, as proposed in TTD (Sutton et al., 2023) and posited in the literature (Tilbury and Flowerday, 2024; Samiolo et al., 2023; Rinta-Kahila et al., 2023). as a guiding framework and qualitative research methodology, to investigate our research question. Understanding this phenomenon and identifying the effects of AI dominance on auditing, would help audit firms, standard setting bodies, professional organizations and audit clients to develop strategies to mitigate the risks and maximize benefits, the auditors to develop requisite skills, and the designers to design the tools that enhance human capability.

Our study provides insights into the evolving role of AI tools in auditing, highlighting both the potential benefits and the risks associated with their use. Audit firms are adopting a cautious approach, focusing on controlled deployment of AI tools to minimize deskilling, while ensuring auditors retain decision-making authority. While AI tools enable efficient task completion, they may inadvertently erode deeper expertise, especially when auditors rely too much on automation and may lead to illusion of competence particularly among early career auditors. Our findings have implications for audit firms' strategies in the deployment and use of AI tools, audit methodology and skills, and the development of governance standards and regulations. Next section provides a review of relevant literature followed by the methodology, findings, discussion and conclusions.

2. Relevant Literature

Technology adoption in auditing is not new and several scholars have studied the adoption, use and impact in different technological contexts. Auditing, however, lags other business sectors in adopting emerging technologies, due to the complexity and repetitiveness of audit tasks, the diverse structures of source documents and data, and the necessity of professional judgment (Oldhouser, 2016).

AI is one such emerging technology that is expected to support auditors' decision-making and have significant impact on the auditing profession. While trying to obtain reasonable assurance about their clients' financial statements, auditors make critical decisions such as assessing the risk and efficacy of internal controls, setting materiality thresholds, evaluation of misstatements, identifying anomalies in financial data, pinpoint inefficiencies in core processes and decide on appropriate procedures and approaches to gather evidence. Unlike other technologies, by automating many of these cognitive tasks, AI is expected to support auditors' decision-making with significant implications for the entire audit eco-system.

Given its nascent stage, empirical studies on the use of AI technologies in auditing are very limited (Dwivedi et al., 2019; Samiolo et al., 2023). Past research predominantly focused on the potential adoption and use of AI technologies in auditing and their implications (Frey and Osbourne, 2017; Susskind and Susskind, 2015; Munoko et al., 2020; Seethamraju and Hecimovic, 2023; Goto, 2021) and research directions (Issa et al., 2016; Borges et al., 2021; Dwivedi et al., 2019; Samiolo et al., 2023, Koreff et al., 2023).

Though implementation of AI-enabled tools is viewed as necessary for the future of auditing, audit firms, regulators and scholars have continued to express concerns (Austin et al., 2021). They include displacement of knowledge workers (Borges et al., 2021; Frey and Osbourne, 2017), effectiveness of the AI tools (Sutton et al., 2023), deskilling of knowledge workers (Triki and Weisner, 2014), and, complacency (Parasuraman and Manzey, 2010), illusion of competency (Fischer, 2015) and bias (Tilbury and Flowerday, 2024) in decision-making.

2.1. Technology Dominance

First developed by Arnold and Sutton (1998), Theory of Technology Dominance (TTD) was used to explain why leading professional services firms have abandoned their attempts to deploy the intelligent systems though they have known potential to reduce labour costs (Susskind and Susskind, 2016; Burton-Jones et al., 2015). It provides a theoretical understanding of the conditions under which knowledge workers were relying on intelligent systems and highlights implications for decision-making. According to TTD, task expertise decreases reliance while the other three constructs – task complexity, familiarity, and cognitive congruence (between system and user) increases users' reliance on technology, with reliance leading to deskilling. Past research on TTD though was limited, focused on the deleterious effects of technology reliance on decision-making and deskilling (Triki and Weisner, 2014). Hampton (2005) and Goddard et al. (2014) have tested

the TTD model and found support for most of the propositions.

An extension of the TTD, called TTD2, was proposed to help understand the complexity of the negative effects (Sutton et al., 2023). Drawing from the literature in several disciplines such as information systems, neuroscience, psychology, and auditing, this extended TTD (TTD2) model aims to explain the underlying causes of technology dominance and to help in the development of systems that might mitigate the underlying deleterious effects of technology dominance (Sutton et al., 2023). TTD2 focuses on three interacting explanatory factors (Furnari et al., 2021) – decision maker (novice vs expert), decision context (experience with system, complexity, repetitiveness) and AI system design (restrictiveness, transparency) and explains how the configuration of these interacting parts lead to deskilling, automation bias, complacency and loss of competence.

TTD2 argues that the higher usage of intelligent systems, that are less transparent would lead to the development of poorer knowledge structure, attrition of users' expertise (loss of competence) and deskilling. Though it is not known in AI context, technology dominance and its related effects such as automation bias, complacency and deskilling were observed in the past in the context of interactive decision aids that support knowledge workers' decision-making (Triki and Weisner, 2014).

2.2. Deskilling and upskilling

Deskilling of most occupations has been taking place for decades due to the division of work, codification and embedding knowledge in work processes through technology (Braverman, 1998). While this deskilling relates to changes to tasks within the occupation, upskilling emphasizes the learning of new technology/system (Martinaitis et al., 2021). Deskilling can occur when auditors lose their previously acquired knowledge due to lack of use, and when new professionals fail to acquire knowledge that is typically gained through experience (Sutton et al., 2023). A study by Samiolo et al. (2023) found that the deliberation, sensemaking and reflexivity required for the professional development of early career auditors would be lost when low value tasks are automated using AI technology. When AI technology is deployed for higher value audit tasks, the ability to use them, however, is dependent upon the experience of working on low value audit tasks (Samiolo et al., 2023).

Deskilling could be countered if AI tools are made more transparent and explainable enabling users to understand and trust them (Hayes and Shah, 2017). Though AI models have steadily been improving their predictive performance (Zhang et al., 2022), their explainability is decreasing (Baryannis et al., 2019). For example, an AI model can identify a list of outliers, but it cannot explain why and what auditors should look for in their investigation. Auditors cannot rely on AI tools when they cannot explain the model's inner workings and outputs, which is a requirement to comply with audit documentation standards (AICPA, 2020; CPAB, 2021; Boland et al., 2019).

Arnold et al. (2023) investigated the effects of explanation on the deskilling of novice users and expertise development. Potential deskilling, they found, can be minimized by reducing cognitive demands on user by conveying automatic explanations, or by designing systems that visually represent expert knowledge, and by matching the explanation format with the knowledge level of users (Arnold et al., 2023). Jensen et al. (2010) found more reliance by novice users than experts and observed that experts are not likely to see the explanations embedded in intelligent systems even if they are available.

2.3. Complacency and bias

Increased reliance on technology could foster complacency and bias that represent different manifestations of the automation induced phenomenon (Lyell and Coiera, 2017; Parasuraman and Manzey, 2010). Automation complacency refers to the tendency to off-load the responsibility of monitoring an automated system with an inflated perception of automation's ability resulting in errors (Cooper et al., 2022; Parasuraman and Manzey, 2010). Automation bias, a key effect of technology dominance, refers to the human tendency to exert less cognitive effort with technology replacing vigilant information seeking and processing (Malaescu and Sutton, 2015: Skitka et al., 2000).

The effects, however, are different depending upon the level of user expertise. Novice users tend to rely more on automation, more vulnerable to manipulation if technology-enabled tools are allowed to influence decision-making (Logg et al., 2019), and tend to overreact and show greater decision bias than experts (Arnold et al., 2006). When required to explore on their own, novice users identified more control weaknesses compared to those relying on the system (Seow, 2011). In a study carried out in tax compliance context, Masselli et al. (2002) found novice users making detrimental decisions when faced with system prompts exhibiting automation bias while experienced users digest the prompts and do not overreact (Noga and Arnold, 2002). Algorithmic bias is another bias inherent in the AI tools (Sun and Madglia, 2019;

Dwivedi et al., 2019). If the quality of data inputs is poor and incomplete, they may inject algorithmic bias which could be amplified by the machine learning algorithms and programming errors, and compromise the reliability of outcomes (Boillet, 2018).

2.4. Competence (loss and illusion)

Cognitive automation enabled by AI tools may exacerbate the erosion of human expertise, weaken human ability to be aware of the activity and lead to loss of competence (Rinta-Kahila et al., 2023). Technology not only feeds human tendency to exert less cognitive effort (Skitka et al., 2000), but also causes people to be less vigilant, promotes a form of mindlessness (Langer, 2014) and result in omission and commission errors (Skitka et al., 2000).

Auditors' potential loss of competence in AI context is exacerbated by the illusion of competence. Illusion of competence is a general overconfidence (Fisher et al., 2015) felt by the user when the technology enables rapid access to guidance on task completion, workflows, policies, and standards in auditing (Dowling and Leech, 2014). This illusion is expected to lead to overestimation of their knowledge resulting in inadequate care to verify the knowledge presented by the tool.

Individuals simply remember where they found the information rather than the information itself (Sparrow et al., 2011). Called 'google effect', this in AI context, means knowing how to execute a task using an AI tool is good enough than knowing how to do it without the tool. This perception could promote the illusion of competence (Tillbury and Flowerday, 2024; Sutton et al., 2023). In a study, Asatiani et al. (2020) found that users who had performed the task using the system were no longer able to perform it on their own when the system was discontinued, or automation failed. Novice auditors admitted that they did not know what they were doing while completing the tasks using that tool (Stensjo, 2020).

Seow (2011) found that users of restrictive systems where the use is mandatory are susceptible to omission errors. In a study by Dowling and Leech (2014), novice level auditors using a restrictive system, felt they were better auditors because of the ease with which they could complete the tasks with the help of technology. Their ability to use the tool, rather than how to make audit decision, created an illusion of competence.

Thus, deskilling, automation bias, complacency and loss of competence are the potential effects of AI use in auditing. While studies discussed in this review pertain to different technological contexts, empirical research on the effects of AI-enabled tools in auditing is essential to understanding how audit practice is evolving. Our study addresses this gap in research.

3. Method

A cross-sectional field study using qualitative research methodology was employed considering the nascent stage of this topic. Cross-sectional field study involves limited-depth studies conducted at a non-random selection of field sites and lies between in-depth case studies and surveys (Lillis and Mundy, 2005). Less structured in data collection than surveys, these studies involve shorter, less intensive data collection. Our approach enables an understanding of the informants' experiences and perceptions on the effects of AI use in auditing and make the context and challenges lucid to the reader (Dyer and Wilkins, 1991). As use of AI in auditing is an intentionally driven change (Weick and Quinn, 1999) the views of decision-makers such as audit partners, technology specialists, and auditors reflect their attitudes, intentions, and perceptions regarding the effects discussed earlier. Using a theoretical, non-random sampling approach, partners, auditors, and technology specialists working in leading auditing firms were chosen as informants, thus having the ability to provide empirical evidence on the issues the study is exploring (Eisenhardt and Graebner, 2007).

Semi-structured interviews were undertaken with a range of stakeholders that include 7 audit partners, 4 auditors/managers and 2 technology specialists working in audit firms. In addition, one leader in a professional organization was interviewed, given that these bodies have an influence on policies and skills related to the use of AI in auditing (see Table 1 for summary respondent profiles). They have 12 years of experience on average in providing audit services.

Table 1: Respondents details

Code	Respondent profile
R1	Senior partner at a Big 4
R2	Senior partner at Big 4 with technology responsibilities
R3	Senior audit partner at Big 4
R4	Technology specialist and adviser to Big-4 firm on emerging technologies
R5	Audit manager at mid-tier firm
R6	Senior audit partner at Big-4
R7	Senior audit manager at Big-4
R8	Senior audit partner at Big-4
R9	Technology specialist at Big-4
R10	Auditor at Big-4
R11	Senior manager at professional organization
R12	Audit partner at mid-tier firm
R13	Audit manager at Big-4
R14	Audit partner at Big-4

A loosely structured interview guide with questions around the key effects – deskilling, automation bias and complacency, and loss of competence, discussed in the literature allowed flexibility to pursue participants' responses. Interviews started with the background and role of the informants in the auditing engagements and in the firms to understand the context and their perspective. Two pilot interviews were conducted to establish and test interview protocol and interview guide (Yin, 2009), and a thematic analysis of the data was carried out independently by both researchers and reconciled. Interviews ranged from 30 to 90 minutes. All the interviews were recorded with prior permission following the ethics guidelines. They were transcribed and verbatim transcripts were sent to individual participants for validation and corrections if any, and then anonymized for analysis. Data from the transcripts was validated by analyzing the transcripts and cross checking with the notes of observations made and analyzed using NVivo software using four factors as the basis. One informant from the Big 4 auditing firm, one independent researcher and a colleague who did not participate in the study reviewed the analysis and a summary of findings. Some examples of the quotes are presented in the findings section.

4. Analysis and findings

The following section discusses the results and findings using the key constructs referred to in the literature review section.

4.1. Deskilling and upskilling

We found that the issue of the influence of technologies on auditors' decision-making and potential deskilling is an ongoing concern with the use of AI tools. Though this technology threatens to partially replace auditors' decision-making capacity and deskilling (Triki and Weisner, 2014; Arnold et al., 2023), respondents believed that the AI enabled tool they use or intend to use, helps them do their jobs better and does "*not to remove from them the need to make decisions and judgments*." (R1). Though audit firms are investing heavily in technology as well as in upskilling auditors, their development and deployment is deliberate and focused (on a narrowly defined audit tasks), and use is controlled. Though scholars have expected their use to be mandatory (Boland et al., 2019; Dowling et al., 2018), focused design, controlled and optional use, and upskilling are the strategies employed by the audit firms to minimize the deskilling effects.

Though mature AI tool is considered necessary, it is not generally made mandatory. The onus of explaining why they are not using the AI tools, however, is left to the individual audit managers, with firms considering this as feedback to help continuous improvement of the AI solution. The purpose, as noted by the respondents, however, *"is not to drive cost savings, but to improve quality and consistency*' (R2) and pitch this to the audit clients. Irrespective of the tool, there is a belief that a manual intervention is necessary. One respondent observed that "*it is never going to be 100% accurate whether you use human or AI, but we need to embed a check in the process – both AI and manual; so, it is the quality benefit that led to the mandate, not the desire for cost savings*" (R2).

Mandatory use is neither a current policy, nor considered practical in audit firms, our study noted. This is primarily because of the evolving nature of the AI-enabled tools (Dwivedi et al., 2021) and the managements' desire to develop tools that are compatible with the user, and focused on narrowly defined audit tasks (Arnold et al., 2023). Explaining the evolving nature of the AI tools, a respondent observed that: "*no matter how hard we try to consider it upfront when we build, once it is launched, we find out a million more things that we need to accommodate before we could make it mandatory at scale. From our experience, its often a multi-year process from the time that we first launched a tool to when it is at a point where it is ready to be mandated. And some of those tools never get to that stage because there is so much diversity for that audit test that it is just wouldn't be practical to mandate*." (R2).

AI tool designed in collaboration with a technical partner is offered as an option to its audit clients in a big-4 firm. A senior partner suggests that "*it is an example of the way we think and the way we want to work; our pitch* (with the client) *would normally be – we will as your auditor keep bringing you new thinking and new tools, and here is an example of something we might do"* (R6). They want this to be an option to the client and "*don't want people to go out and say with XXX firm, you will get that (AI tool) with an audit."* (R6*)* without client's consent. They, however, stress that is a value add to the client and a marketing tool to retain and expand clientele by the audit firms. As noted by a respondent: *"with our iconic clients, it is not actually an audit, it is more like an audit plus. You are providing value to the client to make sure that you remain relevant, and you get access (to client data), and you keep the client*" (R7).

Another strategy adopted by a large firm is to develop a smart audit platform that facilitates development of focused solution for a particular audit task or a series of related audit tasks, standardize it and

roll it over across every audit (R2). Such strategy makes it easy for firms to implement the tool across various audit engagements, derive economies scale for the firm with minimal deskilling effects (Huang and Vasarhelyi, 2019). For example, a Big-4 firm has developed an AI platform that is a scalable vehicle for embedding AI into as many audits as possible. It is now being used by over 10,000 people with the auditors suitably upskilled in this global firm across 14 different countries (R2). Use cases that are focused, scalable, standardized and of relatively low risk are first developed, tested, and made available globally on a platform to provide augmented assistance for achieving efficiencies. The aim is to develop an "*end-to-end process for a certain section of the audit (like an operating expense test or P&E additions where there are a large volume of documents) where AI does first pass on testing and forwards to the auditor for review*," (R2). With this, "*tedious tasks are performed more efficiently by AI, and free up auditors to do more, make judgments in other areas*" (R13). However, challenges such as lack of standardization below certain layers of the audit methodology are limiting their use at scale (R2).

Users would understand and trust the AI tools better if the AI tool is transparent and has explainability (Hayes and Shah, 2017). Though explainability is still not much ingrained in the tools currently in use, audit firms are deploying customizable tools with focus on the visibility of the process and upskilling of auditors. As noted by a senior partner, these tools are developed for a specific area, "*are customizable to meet the needs of the client business*, and "*we frame the tool in terms of what the client would care about and what the audit partners are thinking in terms of audit risks that they want more visibility into to help clients and junior auditors who perform day to day tasks*" (R8). If the processes in the tools "*are like huge black boxes and our audit standards do not require us to go deep into the processes, then we don't go for it*" (R7), because it "*won't be acceptable to audit clients… and won't comply with documentation standards*" (R7), a respondent opined.

Though audit firms have AI tools for specific audit areas, their deployment and use are controlled to make sure they are accepted by the clients, comply with standards, and auditors (novice and expert) are upskilled on technology and understand the process to counter deskilling effects.

4.2. Automation bias and complacency

Audit firms, our study observed, are aware of the potential automation bias and complacency, but believe that these issues can be managed with carefully deployment of AI tool that is designed to augment human capability (Samiolo et al., 2023) and not to replace them or the skills.

Limiting the role of AI tool to mapping and calculations enables audit firms to demonstrate their value to their clients (R1, R6, R8 & R12) and deal with the automation bias and complacency that tool might set in. Respondents believe that the tasks performed by the auditors are mostly diagnostic and focused on a group of related tasks (R1, R6 & R12). Thus, the AI tool they use won't add cognitive load, and therefore the bias it could cause is minimal (Lyell and Coeira (2017). Nevertheless, to minimize the negative implications, one respondent opined that *"I guess, there would be a lot of restrictions on their use in future*" (R14) which include regulations and standards to protect the client's data, AI model design and use, and to counter the potential effects of automation bias and complacency.

Government regulations on AI are still in the development stage and standard setters are well behind technological developments (Seethamraju and Hecimovic, 2022). As noted by a respondent, those bodies have no representation of technologists. Big-4 firms, though have "*a strong technological competence, they don't integrate that into their audit practice*," (R4), instead use it for consulting services. Big 4 firms, for fear of penalties, do not intend to deploy advanced technologies until there are standards and guidance. As noted by a partner, it is '*hard to get some of these techniques (employed in AI tool) to fit with the auditing standards where the thinking is that the computer is a record of the transaction rather than the computer* (AI tool) *is the transaction. Here, it does not record what happened, it* (AI tool) *just makes it happen*" (R6). Audit firms are not willing to take that risk of non-compliance. They are cautious and are ensuring that the users and the AI tool have necessary skills and expertise for the tool to produce sensible outcome and the auditor the ability to review and decide with the skills gained by performing them manually in the past and demonstrate to the client. As R4 observes whilst, "*current thinking and algorithms are trained to replicate the thinking and decision-making of an expert auditor, but we are not yet realising all the benefits AI can bring to audit, as these tools will be requiring auditor*s to explain to regulators *how AI arrive at conclusions*." (R4).

There, however is a dilemma. As noted by a partner, "*we would give the manual jobs to AI, but both the AI tool and the auditor do need experience on those manual processes; if we automate a small portion of audit work with limited data inputs, then AI tool wouldn't have sufficient experience to work efficiently*

and be professionally skeptical; and if we give them (AI tools) *things that involve high judgment, then auditors would lose experience* (R14*).* Audit firms must balance efficiency with expertise retention, as overreliance on AI could lead to a long-term loss of critical auditing skills, therefore a need to preserve auditors' expertise for high-judgment tasks such as assessing management assumptions and methodologies for impairment of assets.

4.3. Loss of competence

Illusion of competence (Sutton et al., 2023) and loss of competence (Rinta-Kahila et al., 2023) are predicted effects of AI use in auditing. As their early career auditors are 'tech-savvy' and with 'upskilling' opportunities, audit firms believe that the potential loss of competence is not a major issue. As noted by a respondent, the "*skills they* (early career auditors*) need to perform those repetitive mundane tasks - can become obsolete in future and won't impact; they are developing so many new technical skills* (upskilling) *anyway*" (R14). With the design of AI tool focused on the automation of repetitive mundane tasks, they believe the benefits outweigh the negative effects as it minimizes the errors early-career auditors may commit in manual processes and is not a real loss of skills (R1, R3, R7 & R9).

Audit firms are cautious in using AI tools. As pointed out by a senior partner "*if large firms go and do something with AI, they will absolutely need to have government approval. If they implement it and then the government comes along and writes a bunch of rules, they can't comply with; they would be back to the old system (R8).* The risk then is non-compliance in the short erm and loss of competence in the long run (Asatiani et al., 2020) as the auditors lost ability to perform without the system. Respondents opined that the auditors are currently in control to decide what data they need to examine and what tool they need to use and audit firms are not willing to let that responsibility and control be vested with an AI-enabled tool. Therefore, the potential loss of competence is limited for now. Although the long-term effects of AI on auditors' competence are not yet fully visible, respondents indicated that the risk of permanent loss of competence exists, particularly among early-career auditors who rely too heavily on AI tools.

5. Discussion

Consistent with prior literature, our study found the potential deskilling effect due to the dominance of AI tools on audit work (Rinta-Kahila et al., 2023; Triki and Weisner, 2014; Arnold et al., 2023). By designing AI tools that are easy for auditors to understand, by making the process visible and matching the skill level of the auditors to use them on a day-to-day basis (Arnold et al., 2023), firms in our study, believe could counter the potential deskilling effects and retain expert knowledge. Though explainability of AI tool is a strategy to minimize deskilling (Arnold et al., 2023), AI tools that are in use now are 'more visible' and helping the auditors to understand and explain the inner workings, which is a requirement under audit documentation standards (CPAB, 2021). As summarized by a respondent, AI tools in use now are mere tools "*that give you the opportunity to be intelligent, mapping out the complete view so that we can understand it, rather than letting the tool make decisions" (R6)*, thus signaling controlled use.

Controlled use, our study found, is deployed by not making the AI use mandatory within the firm for the auditors. It is positioned as an option to audit clients with demonstrable benefits for a possible deployment in audit engagement, if they agree. Audit firms, however, are conscious of not only the deskilling effects, but also the potential tensions with audit clients on sharing of data, models and economic benefits of AI tool (Sun and Madglia, 2019). With widespread use of AI tools in future, these tensions would influence audit fees that may be driven more by the cost of technology than by the audit hours (Austin et al., 2021) and some of the traditional skills lost.

Audit firms, our study observed, acknowledge the influence of automation bias and complacency on audit decision, but believe that these issues can be managed with appropriate training, and carefully deploying a tool that is designed to augment human capability (Samiolo et al., 2023) and not to replace them or the skills. Audit firms are cautious, ensuring that both users as well as the AI tool have the necessary skills and expertise to produce sensible outcomes by matching them (Arnold et al., 2023). Our study concurs with the findings of Samiolo et al. (2023) and suggests that early career auditors may lose the opportunities to make sense of the low-value audit tasks and to reflect on them when they are automated; and that it is essential for novice auditors to have this experience.

Because of the nascent stage of AI use in auditing, loss of competence is not explicitly observed in our study, but it may become evident in the coming years when tools become mature and more powerful, and audit firms under competitive pressure to rely more on them for efficiency and quality gains. Potential loss of competence, for now, however, is minimized by deploying tools that are focused and narrow to do mundane tasks, and by carefully matching the individual skills to the tasks they are assigned to and

by upskilling novice auditors on technology use. There, however, is a concern voiced by several respondents, that early career auditors may lose interest with the mundane tasks, which in turn, may allow complacency and bias to creep in their decision-making (Rinta-Kahila et al., 2023) in the short term and permanent loss of competence in the long run (Stensjo, 2020; Sutton et al., 2023; Asatiani et al., 2020).

Further, current AI technologies cannot support multiple AI components an organization has to deal with (Dwivedi et al., 2021) as they cannot make required changes quickly and reliably to improve the adaptiveness of the models (Walton, 2018). While this may also be a reason for the current crop of AI tools being narrow and focused, in future with more powerful AI tools, this may change and could be deployed for complex tasks that involve judgment with profound impact on the audit profession.

Our findings support the study by Rinta-Kahila et al (2023) and believe that increased reliance on AI in future may foster complacency (Malaescu and Sutton, 2015), generate bias (Lyell and Coiera, 2017), and create illusion of competence (Sutton et al., 2023) in decision-making, fundamentally transforming the audit profession by affecting its professional identity (Susskind and Susskind, 2022, Goto, 2021).

5. Conclusion

Our study empirically tested the potential effects (deskilling, automation bias, complacency and loss of competence) of reliance on audit AI tools on auditors' decision-making and the way firms deal with them. Our findings will help audit firms to develop strategies to help AI tools improve audit decision-making and audit quality and to retain and develop expertise. Such understanding helps in the delineation of the choices audit firms would have in the selection and deployment of AI tools, thereby countering deleterious effects when implemented without such discretion. Our research suggests that technology dominance effects can be addressed by the selection and deployment of appropriate AI tools, their controlled use, visibility of the process, upskilling of auditors, and matching the skill levels with the tools. Our study noticed a perception that audits are now better with the AI tools and that audit firms and auditors would have the ability to use them 'intelligently' to control the outcomes without engendering the audit quality and loss of requisite audit expertise. Though this is contrary to detrimental effects of over reliance on decision aids used in the past on auditors and audit expertise, and may appear optimistic, more critical assessment of these claims through additional data from a range of stakeholders including auditees is required. As AI continued to evolve, further research is required to understand the interactive effects of AI use in auditing across different contexts and experience levels. Only through such critical evaluations can audit firms navigate the complexities of AI use, ensuring both innovation and the preservation of professional expertise in the field. With the AI tools becoming more powerful in future, these effects may be accentuated requiring the stakeholders in the audit-eco system to carefully monitor and control AI use in audit decision-making.

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