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The Risk of Technology Dominance in Using Digital Decision Aids in Assurance Engagements—Evidence from a Survey among Danish Auditors

Dennis van Liempd
Jochen C. Theis
University of Southern Denmark

Steve G. Sutton
NHH Norwegian School of Economics
University of Central Florida

SYNOPSIS: Accounting firms continue to develop digital decision aids (DDAs) that reinforce consistent use of firms' audit methodology and provide assurance for meeting regulator expectations. Firms actively promote use and reliance on DDAs, but relying on such systems risks over-reliance, impacting decision quality and heightening technology dominance. Surveying 725 Danish auditors, we sought to determine the level of reliance practicing auditors have on DDAs and understand how auditors experience these potentially deleterious effects in the field. Results show auditors rely more on DDAs when auditors are inexperienced, task complexity is high, there is familiarity with the DDA, and/or there is cognitive congruence. Junior auditors rely significantly more on DDAs than senior auditors, whereas auditors indicating low usage rely significantly less on DDAs. Overall, senior auditors and auditors not heavily using DDAs have deskilling concerns and are less positive on junior auditors' as well as the profession's skill development when using DDAs.

JEL Classifications: M15; M41; M42.

Keywords: technology dominance; deskilling; automation bias; intelligent systems; digital decision aids; auditing; artificial intelligence.

I. SYNOPSIS AND CONTRIBUTION TO PRACTICE

Over four decades, auditors have steadily increased use of digital decision aids (DDAs)[1] in assurance engagements (Abdolmohammadi 1987; Messier and Hansen 1987; Janvrin, Bierstaker, and Lowe 2008; Dowling and Leech 2014; Brown-Liburd, Issa, and Lombardi 2015; Boland, Daugherty, and Dickins 2019). Most industry reports focus on potential benefits and opportunities of DDAs (e.g., IIR/KPMG 2015; Deloitte 2018, 2019; FRC 2017, 2020), while also using DDAs to increase structure and consistency of audit processes and assure compliance with regulatory

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Dennis van Liempd and Jochen C. Theis, University of Southern Denmark, SDU Business School, Department of Business and Management, Kolding, Denmark; Steve G. Sutton, NHH Norwegian School of Economics, Department of Accounting, Auditing, and Law, Bergen, Norway and University of Central Florida, College of Business, Kenneth G. Dixon School of Accounting, Orlando, FL, USA.

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[1] There are many concepts covering a range of applications and technology, including expert systems, knowledge-based systems, (intelligent) decision aids, (intelligent) decision-support systems, (artificial intelligence (AI)-based) data analytics, and algorithmic decision-making. Here, we use digital decision aids as a general term for these systems.

oversight (Boland et al. 2019; Dowling and Leech 2014; Dowling, Knechel, and Moroney 2018). Despite the many potential benefits, one often overlooked disadvantage is evidence suggesting growing dependence on DDAs leads to technology dominance (Triki and Weisner 2014; Sutton, Arnold, and Holt 2023). Evidence suggests that as DDAs become more structured to force reliance, dominance effects on auditors increase (Dowling, Leech, and Moroney 2008).

Technology dominance is defined as decision-making where the DDA (versus user) takes primary control over the decision process and outcome (Arnold and Sutton 1998). Reliance on DDAs can in the short-term lead to lower audit quality and long-term to deskilling (Arnold and Sutton 1998). The Theory of Technology Dominance (TTD)[2] establishes two ways deskilling occurs: (1) skilled individuals/experts suffer atrophy of skill and knowledge over time from DDA use and reliance, or (2) novice professionals completing similar work traditionally leading to expertise development do not develop the same skills and individual expertise because of the inhibiting nature of DDAs (Sutton et al. 2023). Prior research has revealed loss of declarative knowledge (Dowling et al. 2008; McCall, Arnold, and Sutton 2008; Axelsen 2012), loss of procedural knowledge (Mascha 2001; Axelsen 2012; Eulerich, Waddoups, Wagener, and Wood 2023b), lesser ability to identify errors and use them appropriately (Bible, Graham, and Rosman 2005), more trouble recognizing and compensating for lower-quality documentation (Agoglia, Hatfield, and Brazel 2009; Agoglia, Brazel, Hatfield, and Jackson 2010), reduction in preparer and reviewer independence in audit reviews (Dowling and Leech 2014), myopia in evidence search (Koreff, Baudot, and Sutton 2023), more influence by prior-year working papers yielding lower quality judgments/less accountability (Brazel, Agoglia, and Hatfield 2004), and deteriorating critical thinking skills, professional judgment, and skepticism (Boland et al. 2019).

Surveying 725 Danish auditors,[3] we sought to understand how aspects of technology dominance present themselves in the field. We explore this phenomenon in the audit context, examining the various factors theorized to drive reliance on DDAs.[4] As theorized, results show auditors rely more on DDAs in situations where an auditor is inexperienced, task complexity is high, an auditor is familiar with a DDA, and there is cognitive congruence between the auditor's and DDA's approach to formulating decisions. Exploring deeper, we also find low-seniority auditors rely significantly more on DDAs, as do auditors who routinely use DDAs.

The more concerning parts of TTD are theoretical propositions suggesting heavy reliance can lead to deskilling of auditors using the DDA—either through junior staff not developing knowledge during practice experience that prior auditors would or by senior auditors suffering attrition of audit skills by relying on systems versus their own judgment processes. On the surface, our results show respondents overall have positive views of the influence of DDAs on development of both junior auditors' and the profession's knowledge. This contrasts with theory expecting a negative impact (Arnold and Sutton 1998; Triki and Weisner 2014; Sutton et al. 2023). When this latter aspect is examined more closely, respondents are less positive for junior auditors' development than the profession as a whole, whereas senior auditors and low users of DDAs are more cognizant of junior auditors' deskilling and impeded evolution of the profession's knowledge base.

As researchers begin to explore effects from rapid expansion of DDAs, an increased understanding of how auditors use these systems and the impact of these systems on auditors is needed (Eilifsen, Kinserdal, Messier, and McKee 2020). Auditors, their firms, professional associations, regulators, and other stakeholders surrounding the audit profession should be aware of potential technology dominance pitfalls, so they can be addressed appropriately. Auditors should be in constructive dialogue with data scientists, developers, and suppliers of DDAs to address these problems during the design phase and focus on developing systems supporting improved decision-making while also keeping auditors engaged as contributing partners in decisions and facilitating user skilling rather than deskilling (Arnold, Collier, Leech, Rose, and Sutton 2023).

II. THEORY, RESEARCH QUESTIONS, AND HYPOTHESES

DDAs are a general term for the myriad of systems integrating some form of audit expertise and providing (intelligent) advice to auditors promoting better judgments/decisions. Audit firms have invested significantly in DDA use

[2] Sutton et al. (2023) note that the focus on reliance is about the incorporation of intelligent systems' processes and outcomes into a knowledge worker's judgment and decision processes, a very specialized and parsimonious theorization. This is quite different from the generalized concepts of technology acceptance and use that focus on the willingness to adopt and use an available technology, particularly commercially available applications. There are very robust models that effectively capture this phenomenon (Blut, Chong, Tsigna, and Venkatesh 2022; Hardin, Schneider, and Davison 2022). Rather, the TTD focuses specifically on how AI-based systems affect professional decision-makers (i.e., knowledge workers) (Sutton et al. 2023).

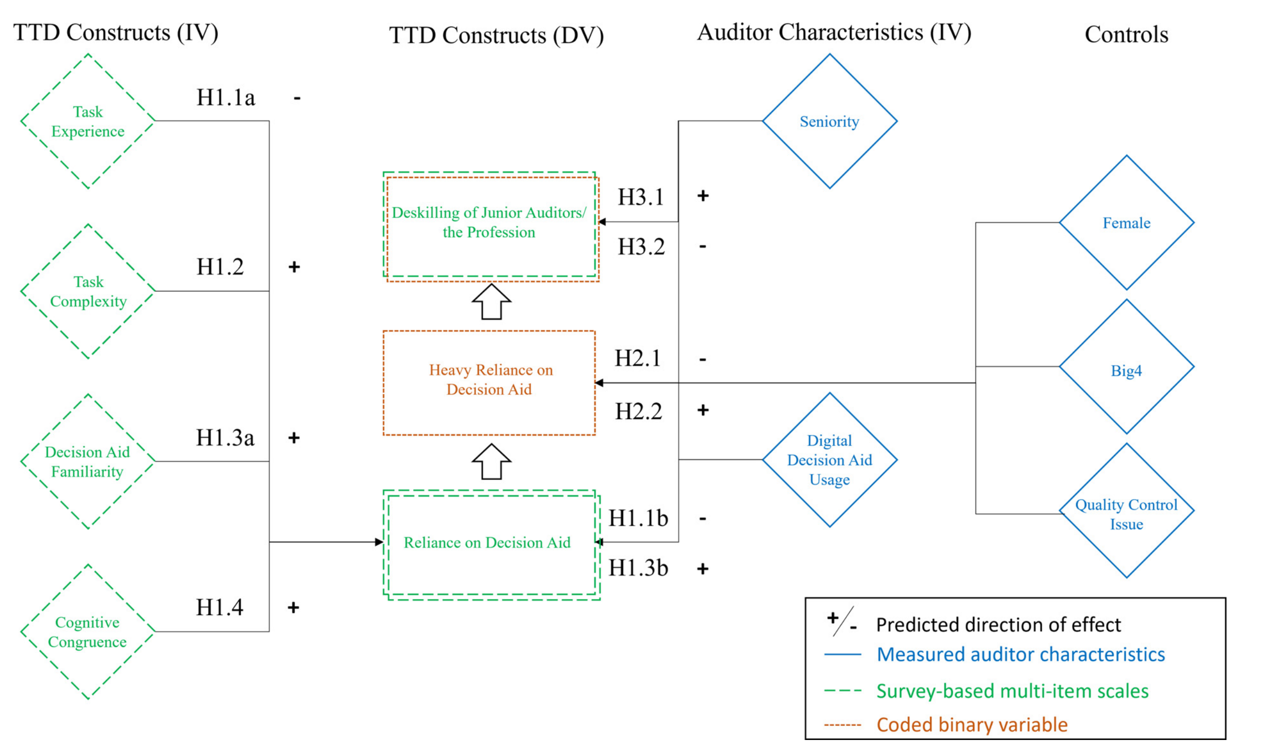
[3] We sought appropriate institutional review board approval for the survey and the study was classified as exempt.

[4] Reliance has become a question mark in the popular press as concerns over "algorithm aversion" have made people question whether auditors will actually rely on DDAs, despite a decades-old literature showing they do (Sutton et al. 2023). Through a systematic set of experiments, Logg, Minson, and Moore (2019) show people almost always exhibit algorithm appreciation rather than aversion. Experienced knowledge-workers are the one exception Logg et al. (2019) identify, but Filiz, Judek, Lorenz, and Spiwoks (2021) show that financial analysts required to use systems began relying on those systems after observing the algorithm outperforming them. Both studies are consistent with the reliance literature evolving from theorizations in TTD (Arnold and Sutton 1998).

(Bell and Carcello 2000; O'Donnell and Schultz 2003; Dowling and Leech 2007, 2014; Dowling 2009) and are encouraged by auditing standards to use DDAs (Janvrin et al. 2008).[5] Auditors in firms of all sizes utilize DDAs to some extent (Rose 2002; Janvrin et al. 2008; Hunton and Rose 2010). Although some have found relatively low DDA use (Bierstaker, Janvrin, and Lowe 2014), usage has increased and although Big 4 traditionally utilized IT more than non-Big 4 firms, they have lost this advantage (Lowe, Bierstaker, Janvrin, and Jenkins 2018). The last decade experienced a new wave of audit DDA use (Gepp, Linnenluecke, O'Neill, and Smith 2018; Eilifsen et al. 2020; Salijeni, Samsonova-Taddei, and Turley 2021; Austin, Carpenter, Christ, and Nielson 2021; Eulerich, Masli, Pickerd, and Wood 2023a) and proposals for further application (Vasarhelyi, Kogan, and Tuttle 2015; Appelbaum, Kogan, and Vasarhelyi 2017; Eulerich, Pawlowski, Waddoups, and Wood 2022).

Already in the 1980s/1990s audit researchers studied intelligent DDAs (e.g., Abdolmohammadi 1987; Messier and Hansen 1987). However, these systems never sustained the great success predicted (Hampton 2005), and questions remain why they did not succeed. Arnold and Sutton (1998) postulate possible explanations through TTD which consists of three stages. Firstly, TTD predicts conditions under which auditors rely on DDAs. Secondly, TTD postulates a short-term risk for technology dominance through over-reliance on DDAs, which long-term can lead to deskilling of the profession and epistemological stagnation (third stage) (Arnold and Sutton 1998; Sutton et al. 2023). The overall theory is visualized in Figure 1.

FIGURE 1
Graphical Summary of the Approach



(The full-color version is available online.)

[5] What the PCAOB and AICPA call computer-assisted auditing techniques are for example mentioned in the PCAOB's AS no. 2201: "An audit of internal control over financial reporting that is integrated with an audit of financial statements," no. 2301: "The auditor's response to the risks of material misstatement," and no. 2401: "Consideration of fraud in financial statement audit." The same goes for the AICPA's AU-C Sections 200–299: "General Principles and Responsibilities with respect to analytical procedures and consideration of fraud," AU-C Sections 300–499: "Risk Assessment and Response to Assessed Risks with respect to more extensive testing," and AU-C Sections 500–599: "Audit Evidence with respect to substantive procedures related to significant related party transactions."

Reliance

Reliance on DDAs is a precondition for technology dominance to occur. Reliance is defined as the degree to which a DDA is integrated as part of a user's decision-making process and influences decision outcomes (TTD). Reliance is difficult to measure, as are over-reliance and under-reliance (Hampton 2005). A specific objective in the development of TTD was to make sense out of a body of research revealing seemingly contradictory results related to reliance, over-reliance, and under-reliance on DDAs and to provide a clear definition of what reliance means. This synthesis of the research lead to a theorization of four factors as the primary drivers of reliance on DDAs (Arnold and Sutton 1998). Prior research (Arnold and Sutton 1998; Triki and Weisner 2014; Sutton et al. 2023) supports reliance as a function of these four factors (the left boxes in Figure 1):

$$\text{Reliance} = f(\text{task experience, task complexity, familiarity with the DDA, cognitive congruence})$$

Our first research question is:

RQ1: Do the factors proposed by TTD influence auditors' reliance on DDAs?

Reliance depends firstly on task experience, defined as the degree of experience a decision-maker has performing a given decision-making task (e.g., a materiality decision), and the degree to which the decision-maker has formed strategies to carry out the task. When users have low to moderate levels of experience, they should rely more on a DDA as they seek help completing the task. The experience dimension is explored in H1.1a and H1.1b (see hypotheses in Table 1).

The second reliance factor is task complexity, defined as the extent to which the task's completion or solution challenges the decision-maker's cognitive abilities. Task complexity is relative; tasks challenging one user's cognitive resources may require less effort for another (Parkes 2017). TTD posits tasks with high complexity lead decision-makers to rely more on DDAs. In short, relying on the DDA requires less cognitive effort than completing the task without (H1.2).

The third reliance factor is DDA-familiarity, defined as the degree to which a user is comfortable with a DDA based on previous experience/training and knowledge of the processes/outcomes embedded in the DDA (Arnold and Sutton 1998). Decision-makers with high-level DDA-familiarity will rely more on the DDA (H1.3a, H1.3b).

TABLE 1

Research Questions and Hypotheses

Reliance

RQ1[a]: Do the factors proposed by TTD influence auditors' reliance on DDAs?

- H1.1a: Task experience has a negative influence on auditors' reliance on DDAs.
- H1.1b: Seniority has a negative influence on auditors' reliance on DDAs.
- H1.2: Task complexity has a positive influence on auditors' reliance on DDAs.
- H1.3a: Decision aid familiarity has a positive influence on auditors' reliance on DDAs.
- H1.3b: Decision aid usage has a positive influence on auditors' reliance on DDAs.
- H1.4: Cognitive congruence has a positive influence on auditors' reliance on DDAs.

Over-Reliance

RQ2: Which auditors exhibit a tendency to rely heavily on DDAs?

- H2.1: Auditors with high-seniority rely less on DDAs than auditors with low-seniority.
- H2.2: Auditors with high decision aid usage rely more heavily on DDAs than auditors with low decision aid usage.

Deskilling and Epistemological Stagnation

RQ3: Which auditors perceive a deskilling effect for junior auditors/the audit profession emerging from DDA reliance?

- H3.1: Auditors with high-seniority perceive a deskilling effect for junior auditors/the audit profession emerging from the reliance on DDAs.
- H3.2: Auditors with low decision aid usage perceive a deskilling effect for junior auditors/the audit profession emerging from the reliance on DDAs.

[a] To respond to RQ1 comprehensively, we operationalize the outlined constructs and associations in two different ways for H1.1 and H1.3 (presented in the following), which is then reflected by two related variants a and b for the respective hypotheses. Variants a of the hypotheses are tested by using survey-based multi-item scales, whereas variants b are tested by considering measured auditor characteristics. Further details are presented in Appendix A.

The fourth reliance factor is cognitive congruence, defined as degree to which problem representation and DDA-processes match mental representation and cognitive processes a user would normally use (Dunn and Grabski 2001). Cognitive congruence represents the perceived similarity between user's and system's preferred decision process and outcome (Al-Natour, Benbasat, and Cenfetelli 2008; Sutton et al. 2023). TTD posits high-level cognitive congruence between decision-maker and DDA promotes reliance (H1.4).

The TTD model viewed reliance from the original engagement with a DDA—a willingness to initiate reliance. This engenders a process view of the reliance decision (Hampton 2005). In the extended TTD model (TTD2, Sutton et al. 2023), reliance is viewed configurationally, that is, the reliance decision changes based on experience using a DDA—the form reliance takes in a professional audit environment where DDA engagement is a daily occurrence. The configurational perspective recognizes the four factors have different levels of influence on reliance based on past DDA experiences. Our hypotheses are consistent with TTD2.

Over-Reliance

Over-reliance occurs when auditors place too much trust in a DDA and take skill-layoffs, allowing the system to make decisions (Sutton et al. 2023). This may result from users not fully understanding the DDA's underlying decision processes (Jensen, Lowry, Burgoon, and Nunamaker 2010), which could lead to full acceptance of the DDAs reasoning without exercising due professional care on the inputs the DDA considered and the veracity of its outputs (Munoko, Brown-Liburd, and Vasarhelyi 2020; Sutton et al. 2023). Users might also not understand the DDA's inherent limitations or how to interpret DDA decision outcomes (Hampton 2005). Accordingly, DDAs can aggravate users' biases. Arnold, Collier, Leech, and Sutton (2004) for example show that intelligent decision aids aggravate bias in novices' decision-making (i.e., lead to poorer judgment) but mitigate bias in experts' decision-making processes, whereas Lombardi, Sipior, and Dannemille (2023) through a literature review show that DDAs can lead to aggravated bias through improper identification of issues, lower levels of skepticism, overconfidence in novices, and inappropriate judgments. All can lead to lower quality decisions with risks exacerbated when tasks are completed under time pressure (Sutton et al. 2023). Auditors operate under time pressure, risking decision-makers will rely too quickly, too much, and too uncritically on system's decision outcomes. Our second research question is:

RQ2: Which auditors exhibit a tendency to rely heavily on DDAs?

During DDA use, novices are susceptible to the *illusion of control* (Langer 1975), an effect making the novice feel in control of decisions when using systems. Novices also overestimate what they know based on prior systems experience making them feel confident they know what they saw the system do—e.g., an *illusion of knowledge* (Fisher, Goddu, and Keil 2015). Experienced decision-makers should have greater awareness across both dimensions (Sutton et al. 2023). We hypothesize high-seniority auditors are less likely to place high reliance on DDAs (H2.1).

One explanation for over-reliance may be automation bias (Skitka, Mosier, and Burdick 1999; Sutton et al. 2023). Automation bias drives errors of omission and commission (Skitka et al. 1999). Errors of omission occur when users fail to react to irregularities or events the DDA does not detect, whereas errors of commission occur when users over-react to DDAs' recommendations, failing to verify with other information or following recommendations despite contrary information. These errors are exacerbated by automation complacency (Parasuraman and Manzey 2010), where users unjustifiably assume DDAs works satisfactorily, resulting in nonvigilance—suboptimal frequency of monitoring and ignoring DDA anomalies, malfunctions, and failures. Heavy DDA reliance breeds complacency, fostering automation bias (H2.2) (Sutton et al. 2023).

Deskilling and Epistemological Stagnation

Continued reliance on DDAs can lead to deskilling (Arnold and Sutton 1998; Munoko et al. 2020; Sutton et al. 2023). Dowling and Leech (2007) interviewed auditors, where one partner stated "auditors don't read the methodology, they don't need to, the system informs them." But the authors note this resulted in auditors just "keying in and doing what it said…rather than thinking about what is required." Auditors risk becoming "system managers"—operators of computer systems—instead of professionals auditing the substance at hand and making professional judgments (Arnold et al. 2004).

Declarative knowledge (auditor's memory of experiences, facts, and their meaning) can deteriorate through long-term reliance on DDAs (Dowling et al. 2008). Dowling and Leech (2014) note novice auditors exhibited an *illusion of knowledge* based on what they could do using DDAs. It is little surprise Westermann, Bedard, and Earley (2015) found audit partners concerned with missed learning opportunities, critical thinking, and professional skepticism due to DDAs.

There is a danger auditors can no longer make decisions themselves without DDAs (Rinta-Kahila 2018). Freeing auditors from routine tasks also frees auditors from what builds expertise. Experienced auditors have good professional skepticism and judgment precisely because they have done years of detailed legwork (Westermann et al. 2015). Our third research question is:

RQ3: Which auditors perceive a deskilling effect for junior auditors/the audit profession emerging from DDA reliance?

Consistent deskilling at individual levels can lead to profession-level epistemological stagnation when applied to a whole generation of auditors. This new generation may no longer be able to generate new ideas for performing audit processes and enhancing the profession's knowledge base (Arnold and Sutton 1998). Essentially all new experts are trained by the same "expert" (i.e., same DDA), creating a myopic view for the profession.

Auditing is recognized as a profession because of its specialized knowledge-base (R. Susskind and D. Susskind 2015). If auditors are replaced by machines and automated systems (Sutton, Arnold, and Holt 2018), systems do not create innovation and knowledge development. This risk increases if DDAs lead to the profession's failure to attract and retain experts (A. Fedyk, Hodson, Khimich, and T. Fedyk 2022), if professionals abandon industries that increasingly replace them with automated systems (Strich, Mayer, and Fiedler 2021). We expect more skilled professionals, less seduced by technology will be better able to perceive these effects (H3.1, H3.2).

III. METHOD

We utilized a quantitative survey method with 725 Danish auditors representing all hierarchical levels from all sizes of audit firms responding to the field-based questionnaire developed for this purpose. We have chosen the survey method for two main reasons. Firstly, experiments often are high in internal validity but can have issues with external validity because of manipulation of hypothetical experimental cases. In the case of deskilling effects that are of high interest in the current study, Dowling et al. (2008) note the lack of experimental control possible in a longitudinal study necessary to capture deskilling and the associated noise that is not controlled as desired in experimental research. Using the survey design ensured capturing data of real-world auditors that are representative for all hierarchical levels in all firm sizes using actual DDAs over an extended period. Secondly, TTD has previously only been tested by experiments and qualitative studies. The experimental studies note the inability to capture long-term impacts effectively in relatively short experimental sessions (e.g., Smedley and Sutton 2007; Arnold et al. 2023). Similarly, qualitative studies more often identify potential TTD effects and call for studies to explore more specifically (e.g., Dowling and Leech 2014; Eilifsen et al. 2020). Thus, using other (quantitative) research methods, like a survey, can help in triangulating the research understanding of a hard to capture effect. Full methodological details and institutional/regulatory background are provided in Appendix A.

IV. RESULTS

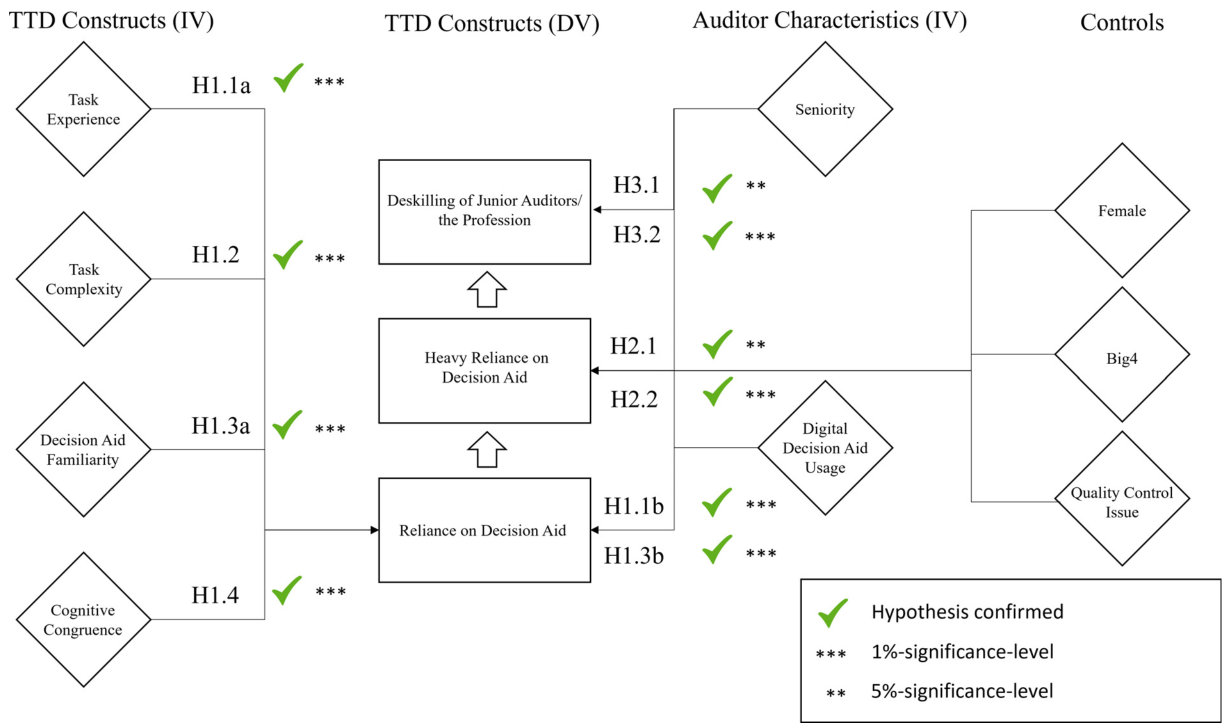
This research is intended to capture a view of the overall TTD model from the perspective of practicing auditors with experience within the profession—a model that with its complexity and integrative nature has been tested in subsets of propositions in past research (Triki and Weisner 2014). Figure 2 provides a visualization of the results as discussed in more detail in the following paragraphs (see Appendix A for more detailed information on analyses).

RQ1 examines whether task experience (H1.1a), task complexity (H1.2), DDA-familiarity (H1.3a), and cognitive congruence (H1.4) influence auditors' reliance on DDAs. Our survey scales (Table 2, Panel A) capture directional influences of each construct on auditors' reliance. Hypotheses are tested comparing mean responses for each construct with scale midpoints using t-statistics.[6] Table 2, Panel A shows t-statistics for all four constructs are significant ($p < 0.01$), supporting hypotheses H1.1a–H1.4.

H1.1b and H1.3b are tested using "seniority" and "Digital Decision Aid (DDA) usage" as proxies for TTD-constructs task experience and DDA-familiarity. Table 3 shows subsample means by seniority and DDA usage for dependent variable *reliance*. Means for *reliance* on high- versus low-seniority are significantly different ($p < 0.01$). Mean differences for *reliance* on high versus low *DDA usage* are also significant ($p < 0.01$). High-seniority auditors rely significantly less (H1.1b) whereas auditors with high DDA usage rely significantly more on DDAs (H1.3b). Results confirm task experience has a negative, whereas task complexity, DDA-familiarity, and cognitive congruence have positive influences on auditor reliance.

[6] We report two-tailed p-values unless stated otherwise.

FIGURE 2
Visualization of the Results



(The full-color version is available online.)

TABLE 2
Scales, Items, and Summary Statistics

Panel A: Reliance Factors

Scale *Item*	**Question and Response Options**	**Mean [n]**	**Std. Dev.**	**Cronbach's Alpha**
On a scale from 1 (strongly disagree) to 5 (strongly agree), how much do you agree with the following statements:				
Experience		3.0839 [566]***	0.7074	0.0099
When I was younger, I relied more on digital decision aids.				
Digital decision aids allow me to make professional judgments in areas where I have limited experience.				
Task Experience		3.2530 [565]***	0.7948	0.7767
When I have limited experience with a specific audit task, digital decision aids tend to make me more confident in my professional judgments.				
Digital decision aids allow me to make professional judgments in areas where I am not an expert.				
Task Complexity		3.3256 [565]***	0.8537	0.8004
When a specific audit task is complex, digital decision aids tend to be particularly useful in helping me complete the task.				
When the audit task is very complex, I rely more on digital decision aids.				

(continued on next page)

TABLE 2 (continued)

Scale *Item*	Question and Response Options	Mean [n]	Std. Dev.	Cronbach's Alpha
Decision Aid Familiarity		3.8858 [565]***	0.6962	0.7614
When I know the digital decision aid well from previous experience, I tend to be more confident in my professional judgments				
When I have used the digital aid with ease before, I apply it more in my assessments.				
Cognitive Congruence		3.6663 [565]***	0.7100	0.8224
When the digital decision aid tackles a task in the same way I would have done, I tend to be more confident in using it.				
When the digital decision aid has generally come to the same conclusion as me when I have used it in the past, I rely more on it.				

*** Indicates mean differs significantly ($p < 0.01$) from midpoint of the scale (two-tailed t-statistic).
Untabulated analyses furthermore reveal that the presented results remain largely unchanged if the analyses are repeated for subsamples comprising responses of male versus female auditors, auditors working for Big 4 versus non-Big 4 firms, and auditors on the five hierarchical levels captured (see Table A1, Panel B).

Panel B: Reliance and Deskilling

Scale *Item*	Question and Response Options	Mean (n)	Std. Dev.	Cronbach's Alpha
On a scale from 1 ((nearly) never) to 5 ((nearly) always), how often do you experience the following situations:				
Reliance		2.5675 (533)	0.6461	0.8676
When the DDA produces an assessment, for example on the materiality amount, I use it even if I actually think otherwise.				
Even when I don't really understand how the digital decision aid works, I tend to trust its output.				
When the digital decision aid comes up with what I already thought in advance, I don't need more substantive testing (such as additional testing of transactions, for example).				
Using digital decision aids is the best way to make professional judgements.				
Using digital decision aids greatly reduces the risk of assessments.				
I trust the results of digital decision aid more than my own judgment.				
It can be difficult for me to make my professional judgments without digital decision aids.				
I am not at all worried about errors when I have used digital decision aids in my assessments.				
Digital decision aids almost completely eliminate the need for additional detailed testing, such as transaction testing.				
Digital decision aids almost completely eliminate the likelihood of incorrect assessments.				
I believe that in the long run, the use of digital decision aids will: (1 much worse to 5 much better)				
Deskilling of Junior Auditors [The Profession]		3.2122 [3.4234] (556)	0.8157 [0.7480]	0.9020 [0.9244]
Make junior auditors' [*the profession's*] *audit knowledge:*				
Make junior auditors' [*the profession's*] *client knowledge:*				
Make junior auditors' [*the profession's*] *professional judgments:*				
Make junior auditors' [*the profession's*] *knowledge of the audit process:*				
Make junior auditors' [*the profession's*] *innovation in audit:*				
Make junior auditors' [*the profession's*] *learning in auditing:*				
Make junior auditors' [*the profession's*] *ability to find new solutions:*				

RQ2 queries which auditors exhibit tendencies to rely heavily on DDAs. We use participants' responses on the DDA *reliance* scale to code the binary variable *Heavy Reliance* (see Appendix A). To test H2.1 (auditors with high-seniority rely less) and H2.2 (auditors with high DDA usage rely more), we conduct a logistic regression with *Heavy*

TABLE 3

Subsample Mean Comparisons

Scale	**Subsample Means [n]**		**Mean Comparison**
	Seniority		**Two-Tailed t-stat**
	High	**Low**	**p-value**
Reliance	2.495 [400]	2.785 [133]	0.0000***
Deskilling of junior auditors	3.149 [416]	3.400 [140]	0.0016***
Deskilling of the profession	3.408 [416]	3.469 [140]	0.4012
	DDA usage		**Two-Tailed t-stat**
	High	**Low**	**p-value**
Reliance	2.680 [285]	2.438 [248]	0.0000***
Deskilling of junior auditors	3.362 [296]	3.041 [260]	0.0000***
Deskilling of the profession	3.577 [296]	3.248 [260]	0.0000***
	Combined: *High Seniority* and		**Two-Tailed t-stat**
	High DDA usage	***Low DDA usage***	**p-value**
Reliance	2.614 [220]	2.350 [180]	0.0000***
Deskilling of junior auditors	3.328 [227]	2.934 [189]†	0.0000***
Deskilling of the profession	3.593 [227]	3.186 [189]	0.0000***

*** Indicates significance at the 1 percent level.
† Indicates mean's difference from the midpoint of the scale (i.e., 3) is marginally significant ($p = 0.121$; one-tailed t-statistic).
Untabulated analyses furthermore reveal that the presented results remain largely unchanged if the analyses are repeated for subsamples comprising responses of male versus female auditors and auditors working for Big 4 versus non-Big 4 firms.

Variable Definitions:
Seniority = a binary variable, it assumes the value 1 ("high") if participants indicate their current hierarchical level to be (senior) manager or higher (see Table A1, Panel B), and 0 ("low") otherwise; and
DDA usage = participants whose responses are above the mean for the scale "Digital Decision Aid Usage" (see Table A3) are assigned the value 1 ("high"), and participants whose responses are below the mean are assigned the value 0 ("low").

Reliance as the dependent variable, *Seniority* and *DDA usage* as independent variables, and control variables *female*, *Big4*, and *quality control issue* (Table 4). The odds ratios for both *Seniority* (0.5426) and *DDA usage* (1.6509) are significant ($p < 0.01$). Results confirm H2.1 and H2.2, the probability to belong to the "heavy reliance" group is significantly lower for auditors with high-seniority, but significantly higher for auditors with high DDA usage.

RQ3 explores which auditors perceive deskilling effects for junior auditors/audit profession from DDA use. We first provide mean comparisons for dependent variables "deskilling" of junior auditors and the profession, divided by *Seniority* and *DDA usage*, as well as by *DDA usage* for auditors with high-seniority only (hence, combined) (Table 3). Subsample means for senior (versus junior) auditors and auditors with low (versus high) DDA usage are, with one exception, significantly lower for both deskilling of junior auditors and the profession. However, cell means are generally above the scale midpoint (i.e., 3). This implies, overall, DDAs are seen as having a positive rather than a negative effect on (junior) auditors' skills. This finding is not surprising given TTD2's explanation of underlying causes and effects of deskilling where TTD2 posits DDA use provides novice users with inflated views of what "they know" versus what "they can do using the DDA." Considering auditors with high-seniority only and comparing subsample means for those exhibiting a high versus low DDA usage, the mean for deskilling of junior auditors in the subsample of senior auditors with low DDA usage is below the scale midpoint (2.934; $p = 0.121$, one-tailed). These marginally significant results indicate senior auditors with low DDA usage tend to perceive a deskilling effect of DDAs on junior auditors.

For a more refined evaluation of the relationships, we conduct logistic regressions with deskilling perceptions of junior auditors and the profession as dependent variables, respectively. *Seniority* and *DDA usage* are independent variables (Table 4). Results show having high-seniority increases, whereas exhibiting high DDA usage decreases, the

TABLE 4

Logistic Regressions

Dependent Variable	***Heavy Reliance***	***Deskilling Perception Junior Auditors***	***Deskilling Perception Profession***
Independent Variable		**Odds Ratio**	
Seniority	0.5426***	2.1428***	1.7669**
DDA usage	1.6509***	0.5301***	0.4303***
female	0.9925	1.1836	1.3591
Big4	0.6572**	1.2885	0.9658
quality control issue	0.7634	1.1426	1.1802
Constant	1.5952**	0.4175***	0.2465***
n	589	535	512
Pseudo R^2	0.0280	0.0334	0.0360

***, ** Indicate significance at the 1 percent and 5 percent level, respectively (two-tailed).

Variable Definitions:
Heavy Reliance = a binary variable, it assumes the value 1 if participant's response is above the mean for the scale "Reliance" (see Table 2, Panel B), and 0 otherwise;
Deskilling Perception Junior Auditors/Deskilling Perception Profession = a binary variable, it assumes the value 1 if participant's response is below the midpoint of the scale (i.e., 3) "Deskilling of Junior Auditors/the Profession" (see Table 2, Panel B), and 0 otherwise;
female = a binary variable, it assumes the value 1 if participants indicated their gender to be female, and 0 otherwise;
Big4 = a binary variable, it assumes the value 1 if participants indicated that they work for a Big 4 firm (see Table A1, Panel A), and 0 otherwise; and
quality control issue = a binary variable, it assumes the value 1 if participants responded that they received comments in their most recent internal or external quality control for their assurance engagements.

probability of belonging to the group perceiving deskilling of junior auditors ($p < 0.01$). Results for dependent variable *Deskilling Perception Profession* are comparable, with odds ratio for seniority being significant at $p < 0.05$. Findings imply auditors with high-seniority and auditors with low DDA usage tend to perceive a deskilling effect for junior auditors and the profession emerging from DDA reliance, providing support for hypotheses H3.1 and H3.2.[7]

V. CONCLUSION

Audit firms increasingly embed DDAs into audit processes and these DDAs are becoming more intelligent (Dowling and Leech 2007; Eilifsen et al. 2020). Although structured audit processes have advantages in maintaining consistent audit strategy, achieving minimum acceptable quality levels and conformance to regulators' expectations (Dowling et al. 2018; Boland et al. 2019), there is evidence DDAs lead to deskilling (e.g., Dowling et al. 2008; Goddard, Roudsari, and Wyatt 2014). Through a survey of 725 Danish auditors, we sought to determine the level of reliance on DDAs and understand how auditors experience potentially deleterious effects in the field. Our study was based on TTD's core propositions and results support theorized relationships.

First, we find the four factors (task experience, task complexity, DDA-familiarity, and cognitive congruence) theorized to enhance reliance on DDAs are perceived by our audit participants to drive reliance. Second, although overall findings reveal lower perceptions of junior auditors' expertise development (but not necessarily deskilling), when we focus on the subset of respondents with high-seniority/experience and those with low DDA usage (subsets potentially more skeptical), we find stronger concerns over deskilling of junior auditors and stagnation of knowledge growth in the profession.

There are several implications of our research findings for researchers and audit stakeholders. All should be aware of probable deskilling effects eroding the knowledge-bases of professionals rising in the firms. Both researchers and professionals should seek better ways of designing systems that alleviate these deskilling effects—ideally promoting skilling of DDA users during use of production systems (i.e., through normal audit completion using DDAs). Arnold et al.

[7] To test the robustness of our results, we repeat all previously outlined analyses containing the variable *Seniority* after replacing it with the variable *Super-seniority*. *Super-seniority* is a binary variable assuming the value 1 ("high") if participants indicate their current hierarchical level to be certified auditor or higher, and 0 ("low") otherwise (see Appendix A for details). Although the odds ratio for *Super-seniority* in the logistic regressions with deskilling perception of junior auditors and the profession, respectively, become (marginally) insignificant, all other inferences remain largely unchanged. We furthermore repeat the previously outlined analyses with a different operationalization of the variable *DDA usage* (see Appendix A, especially section "*Influence Factors*"), and inferences again remain largely unchanged.

(2023) provide one such example of research in this area, enhancing novice acquisition of skills through knowledge-based interface design and automatic provision of user-appropriate explanations. Other methods need to be explored.

This is even more important from an AI perspective, because one inhibitor of human collaboration in audit decision-making is the unexplainable nature of the most effective AI techniques. This necessitates a focus on developing highly effective AI techniques that are explainable and where auditors can understand how recommendations are formulated (Zhang, Cho, and Vasarhelyi 2022). Traditionally, researchers attempt to address communication of underlying decision-logic to users by building explanation facilities into such systems. However, research emphasizes the need for such explanations to be matched with users' level of expertise to facilitate effective data-entry by novices and effective review and evaluation by experts (Arnold, Clark, Collier, Leech, and Sutton 2006).

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APPENDIX A

Methods and Supplementary Information

Survey Design

Influence Factors

The overall structure of our analyses and the relationship between the constructs is depicted in Figure 1. We capture five constructs inspired by the TTD as our first set of influence factors with the scales outlined in Table 2, Panel A: experience, task experience, task complexity, DDA-familiarity, and cognitive congruence (Arnold and Sutton 1998). All constructs were measured through two-item scales where participants indicated their agreement with the respective statements on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). For each construct, we generate the summative scale from the corresponding items and report scale means, as well as Cronbach's alpha in Table 2, Panel A. Cronbach's alpha provides a measure of the internal consistency—which is an indicator of reliability—of our scales and describes the extent to which the items in the scale measure the same construct (Tavakol and Dennick 2011; Revicki 2014; Taber 2018; Cronbach 1951). A general accepted rule is that Cronbach's alpha values of 0.60–0.70 indicate an acceptable level of reliability; values of 0.8 or greater indicate very good levels (Ursachi, Horodnic, and Zait 2015). Given that the task experience as well as DDA-familiarity scale reach alpha values of above 0.75 and the task complexity as well as cognitive congruence scale reach alpha values above 0.80, we conclude these scales have acceptable to very good levels of reliability. The experience scale has a very low Cronbach's alpha value and is consequently not further considered in the analyses due to reliability concerns.

As a second set of influence factors, we captured auditor characteristics to code the variables *Seniority* and *DDA usage* as proxies for the TTD-constructs task experience and DDA-familiarity, respectively. *Seniority* is a binary variable and assumes the value 1 ("high") if participants indicate their current hierarchical level to be (senior) manager or higher (see Table A1, Panel B), and 0 ("low") otherwise.[8] Furthermore, participants whose responses are above the mean for the underlying DDA usage variable are assigned the value 1 ("high"), and participants whose responses are below the mean are assigned the value 0 ("low"). The underlying DDA usage variable is a summative scale based on a block of questions that asks participants to indicate their use of different types of DDAs during assurance engagements (see section "Use of DDAs in Denmark" further below for details).[9]

Finally, we include additional auditor characteristics—*female*, *Big4*, and *quality control issue*—into the analyses as control variables, because they could potentially influence our dependent variables, without being of specific interest for our study. Specifically, *female* is a binary variable and assumes the value 1 if participants indicated their gender to be female, and 0 if participants indicated their gender to be male. *Big4* is a binary variable and assumes the value 1 if participants indicated that they work for a Big 4 firm (see Table A1, Panel A), and 0 otherwise. *quality control issue* is a binary

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8 In additional robustness checks, we furthermore use the variable *Super-seniority*, which is a binary variable and assumes the value 1 ("high") if participants indicate their current hierarchical level to be certified auditor or higher (again, see Table A1, Panel B), and 0 ("low") otherwise.

9 The underlying digital decision aid usage variable is the summative scale of all items of Table A3. Cronbach's alpha for the summative scale is 0.8978, indicating a very good level of reliability. For a robustness check we repeated our analyses with a different operationalization of the underlying *DDA usage* variable. Specifically, we asked participants the following question: "In a typical assurance task, according to your best estimate, to what extent is your final assessment/conclusion based on guidance from digital decision aids?" (on a scale from 1 ((nearly) never) to 5 ((nearly) always)), and again coded *DDA usage* as a binary variable based on a mean split. The inferences based on the presented results remain largely unchanged.

APPENDIX A (continued)

TABLE A1

Participant Demographics

Panel A: Gender, Age, Audit Firm

Item	Mean (Min.; Max.) or Absolute [% of Participants]
Number of usable responses	725
Please indicate which task you work with (alone or in a team) [multiple responses possible]	
Auditing	702 [96.83%]
Review	433 [59.72%]
Extended review	593 [81.79%]
What is your gender?	
Female	204 [28.14%]
Male	520 [71.72%]
Other	1 [00.14%]
What is your age?	*42.48 (20; 81)*[a]
For which audit firm do you work?	
Deloitte, PwC, E&Y, KPMG	153 [21.10%]
BDO, Beierholm	118 [16.28%]
Grant Thornton, Martinsen, Redmark, Info:revision, Partner Revision, Christensen Kjærulff	72 [09.93%]
Medium-sized audit firm (more than 5 partners, but not mentioned above)	138 [19.03%]
Small audit firm (2–5 partners)	196 [27.03%]
One-man firm (1 partner)	48 [6.62%]

[a] Two participants indicated they were "99" and "999" years old. These observations were excluded for the calculation of the mean and the range.

Panel B: Auditor Level and Experience

Item	Mean (Min.; Max.) or Absolute [% of Participants]
Your current hierarchical level can be best described as:	
(Owner-)Partner	219 [30.21%]
Certified auditor (reviews audit work, makes significant audit decisions and signs off)	131 [18.07%]
(Senior) Manager (helps plan the audit, leads the audit, reviews work and works with the client)	170 [23.45%]
Auditor (responsible for audit fieldwork, including supervision and performance of detailed work activities)	122 [16.83%]
Assistant/student/trainee (performs most detailed work)	83 [11.45%]
For how many years in total have you:	
Worked as an auditor (all hierarchical levels):	*19.53 (0; 60)*[a]
Worked as a certified auditor (enter 0 if you are not a certified auditor):	*17.95 (0.5; 45)*[b]
Approximately how many auditors (certified and noncertified) are employed at your local office?	*73.16 (1; 2,500)*
At your best estimate, how many clients (both assurance and nonassurance) do you currently have in total?	*248.70 (0; 15,000)*

[a] One participant indicated s/he worked "99" years as an auditor. This observation was excluded for the calculation of the mean and range.
[b] Observations where participants indicated "0," and one observation where the participant indicated s/he worked "99" years as a certified auditor were excluded for the calculation of the mean and the range.

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APPENDIX A (continued)

variable and assumes the value 1 if participants responded that they received comments in their most recent internal or external quality control report for one of their assurance engagements.

Dependent Variables

We capture four constructs inspired by the TTD as our dependent variables (see Table 2, Panel B). *Reliance* on decision aid is a multi-item scale (summative scale), where participants indicated how often they experience the situations outlined in the items on a five-point Likert scale ranging from 1 ((nearly) never) to 5 ((nearly) always). Reliance is not directly observable as argued in TTD, and application of latent constructs focusing on attributes of reliance are preferred even in experimental studies testing TTD (Hampton 2005). We differentiate between auditor perception of *Deskilling Perception Junior Auditors* versus *Deskilling Perception Profession* (in general) and capture responses with two separate summative multi-item scales, where participants indicate on a five-point Likert scale the extent they believe in the long-run that use of DDAs will make junior auditors versus the profession much worse (1) versus much better (5) in various domains (items). The Cronbach's alpha values for the three scales range from 0.86 to 0.92, indicating very good levels of scale reliability (Ursachi et al. 2015). To gain additional insights, we use captured auditor responses for the *reliance* scale to code a binary variable representing the construct *Heavy Reliance* (on decision aid). The variable assumes the value 1 if participant's response is above the mean for the scale *reliance* (see Table 2, Panel B), and 0 otherwise. Similarly, we captured auditor responses on scales for auditor perception of *Deskilling Perception Junior Auditors* versus *Deskilling Perception Profession* to code two binary variables representing the constructs deskilling perception junior auditors and deskilling perception profession. The variables assume the value 1 if participant's response is below the mean for the scales on *Deskilling Perception Junior Auditors* and *Deskilling Perception Profession*, respectively (see Table 2, Panel B), and 0 otherwise.

Participants

Recruitment Process and Response Rate

The survey was intended for all external auditors in Denmark who work with assurance engagements. Denmark's accounting industry has approximately 17,000 full-time employees, but besides auditors, this includes accountants, bookkeepers, and tax advisers. It is unknown how many do assurance engagements, and there is no standard database to use. We collected potential emails for administering the survey electronically in two ways. Firstly, the Danish professional association FSR-Danish Auditors provided us with a list of members who are state-approved auditors in Denmark. There are approximately 3,000 state-approved auditors in Denmark, of which 85 percent are FSR members. Secondly, we hand-collected available employee email addresses from 124 Danish audit firms (excluding auditors on first list, secretaries, tax employees, and other nonauditors), mainly from firm websites. These firms represent over 80 percent of total Danish audit industry revenue (and over 90 percent of total audited companies' revenues). A total of 7,443 emails linked to the survey were sent out in December 2021 and January 2022; 2,363 based on the FSR list and 5,080 based on the manual list (see Table A2). From 7,443 initially addressed individuals, we record 1,894 as unavailable (undeliverable, auto-reply/out-of-office, or do not wish to participate) and arrive at a net total of surveys sent of 5,549. Participants not responding to our survey and not recorded as unavailable were reminded of the survey up to two times. Eight hundred eight participants responded to our survey (14.56 percent). Of these, 83 participants indicated they are not working with assurance engagements, which provides us with 725 usable responses. Of those, 192 participants provided partial responses,[10] whereas 533 participants (9.61 percent) completed the entire survey.[11]

Participant Demographics

Participant demographics are presented in Table A1, Panels A and B. Of the 725 participants, 28.14 percent are female.[12] Participant ages range from 20 to 81, with the average being 42.48.[13] Participants on average worked as an

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[10] Participants with partial responses begin to drop out of the survey after having answered the first six questions of the survey.

[11] We test for a nonresponse bias by differentiating between different waves of responses (Armstrong and Overton 1977). Specifically, we repeated our analyses for a subsample comprising of the second wave of responses that were received only after a reminder was sent out to participants. This subsample comprises of about 45 percent of the total number of responses. Generally, there were several days between the first and second wave of responses where we did not record any response. The results for the subsample of late respondents are generally comparable to the presented analyses in all material regards.

[12] One participant indicated the gender to be "other" than female or male.

[13] Two participants indicated they were "99" and "999" years old, respectively. These observations were excluded for the calculation of the mean and the range.

APPENDIX A (continued)

TABLE A2

Response Rates

Position	n	Share of Total Surveys Sent (Net)
Manual list—surveys sent	5,080	
FSR list—surveys sent	2,363	
Total surveys sent	**7,443**	
Undeliverable	69	
Auto-reply, out-of-office	413	
Do not wish to participate	1,412	
Total not available	**1,894**	
Total surveys sent (net)	**5,549**	
Total responses	**808**	**14.56**%
No assurance engagements	83	
Usable responses	**725**	**13.39**%
Partial responses	192	
Full responses	**533**	**9.61**%

auditor for 19.53 years and as certified auditors for 17.95 years.[14] Of the participants 30.21 percent, 18.07 percent, 23.45 percent, 16.86 percent, and 11.45 percent indicated their current hierarchical level best described as (owner-)partner, certified auditor,[15] (senior) manager, auditor, and assistant/trainee.[16]

Furthermore, 21.10 percent of the participants work for Big 4 firms, 26.21 percent work for one of the eight next larger Danish audit firms, 19.03 percent work for a medium-sized audit firm (more than 5 partners), and 33.65 percent work for small audit firms (one to five partners). Average number of auditors (certified and noncertified) employed at participants' local office is 73.16, whereas the average number of clients (both assurance and nonassurance) that participants estimate they currently have is 248.70.[17]

Institutional Landscape in Denmark

As with most major western country economies, Denmark participates in the global audit market with a mix of engagements requiring adherence to international and U.S. audit standards with numerous companies registered on applicable stock exchanges.[18] Statutory audits in Denmark are regulated depending on the nature and size of the company. Danish listed companies are required to apply EU-endorsed IFRS in their (consolidated) financial statements. With respect to the audit, firms with EU-listed equity or debt instruments and certain financial services companies are considered Public Interest Entities (PIEs) and therefore regulated by the EU Regulation for PIEs. Where the PIE-regulation includes options for nations to apply more or less strict rules, Denmark has chosen minimum implementation. Other companies are divided into reporting classes and are regulated by the EU Accounting and Audit Directives, implemented into national law through the Financial Statements Act (*Årsregnskabsloven*) and the Auditor Act (*Revisorloven*). Denmark has not adopted IFRS for small and medium-sized entities. Small, medium-sized, and large companies are required to have a statutory audit (sole proprietorships and very small firms are exempt from audit).[19]

The title State Authorized Public Accountant (SPA; *Statsautoriseret Revisor*) is protected by the Auditor Act, and only SPAs can sign the audit report. Auditing financial institutions requires an additional certification by the Danish Financial

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[14] One participant indicated s/he worked "99" years as an (certified) auditor. This observation was excluded for the calculation of the means.
[15] Certified auditors are CPAs, licensed by the state to sign audit reports.
[16] Because labels for different hierarchical levels may differ across firms, we added brief descriptions of the main tasks generally performed on the respective level (see Table A1, Panel B, for details).
[17] Admittedly, the respective question capturing the average number of clients is prone to being misunderstood, and consequently, the presented figure should be interpreted carefully (see Table A1, Panel B). Although we intended to get at the number of current clients at an *individual level*, responses suggest that a share of participants must have indicated estimated number of clients on the *office or even firm level*.
[18] As of the writing of this manuscript, four Danish companies are listed on the NASDAQ or NYSE and 28 companies are registered for OTC.
[19] Small companies can opt to have a uniquely Danish assurance engagement, called Extended Review (*Udvidet Gennemgang*). Even though this extended review legally is considered to be an audit equivalent, it only gives limited assurance.

APPENDIX A (continued)

Supervisory Authority (DFSA). In most ways, the specific requirements in the audit regulations mirror professional global requirements with respect to specific demands for auditors' education[20] and experience, for licensing, and for professional duties and responsibilities, elevated to mandatory legal status, including penalties for breaches of conduct.

According to RL §16, Danish auditors must meet "good auditor practice" (*god revisorskik*). This means audits must be conducted in accordance with the global International Standards on Auditing (ISA) as issued by the IAASB and translated by the FSR, the Danish professional audit association. Audit oversight and quality assurance is exercised by the DFSA for financial institutions and by the Danish Business Authority (DBA) for all other companies. The DBA is a member of both the Committee of European Auditing Oversight Bodies (CEAOB) and the International Forum of Independent Audit Regulators (IFIAR).

All audit firms in Denmark were of Danish origin until the 1960s, where Price Waterhouse and Arthur Andersen as part of their international strategy joined the Danish audit market. In the 1970s and 1980s, the larger, Copenhagen-based Danish audit firms expanded their position nationally and began to establish loose connections with international audit firms (Christiansen and Loft 1992). Nowadays, internationalization and concentration have resulted in harmonization with international networks' management structures and technical issues. All Big 4 firms as well as most other international networks are present in Denmark. The Big 4 produce more than half of total audit market revenue (Egholm 2022).

Basically, all Danish audit firms have access to DDAs as part of their audits. The Big 4 audit firms and other international audit firms such as BDO, Grant Thornton, Baker Tilly or Crowe Horwath in Denmark apply the same (proprietary) DDAs as other member firms of the respective worldwide network. Many other Danish firms have merged forces with international accounting and advisory network; top-ten firms Beierholm with HLB (Beierholm 2023) and Martinsen with the PrimeGlobal network (Martinsen 2023),[21] for example. Most, if not all international networks have the topic of DDA usage high on their agenda (e.g., HLB 2019; PrimeGlobal 2023).

Furthermore, audit firms that do not use tailor-made DDAs provided through their network, will purchase software solutions from respective providers. The most used audit software in Denmark across all firm sizes is Caseware. In a survey of 288 Danish certified auditors (Liempd, Kristensen, Wickstrom, and Haug 2020), 21 percent used a software package specifically designed by the (international network) firm, whereas 65 percent of respondents used Caseware[22] (15 percent of which had adapted it specifically to their firm). Caseware, just as other relevant competitors, offers a variety of solutions to audit firms, ranging from software packages for managing audit working papers to comprehensive audit analytics platforms (Caseware 2023).

Use of DDAs in Denmark

Against this background, to assess the validity of our survey results it is important to understand what experience participants *de facto* have with the use of DDAs. We asked participants to indicate use of different types of DDAs during assurance engagements. Specifically, we asked "How often do you use the following digital decision aids during assurance engagements?" and captured responses on a scale from 1 ((nearly) never) to 5 (very often). As response options, we provided brief, general descriptions of the most important DDA types currently available to auditors, which we derived from Dowling and Leech (2007). For a more granular picture, we provide mean responses in Table A3 not only for the overall sample, but also for subsamples of large versus medium versus small firms as well as for auditors with high- versus low-seniority.

The descriptive results presented in Table A3 suggest that, on average and for the overall sample, our participants use most types of DDAs at least occasionally (i.e., means above the midpoint of the scale). Although some simpler DDAs (electronic questionnaires and/or checklists, digital tools that help assess client acceptability and/or independence, as well as digital materiality calculators) are used more frequently (means above 4 representing "often"), in particular more advanced DDAs (e.g., digital tools that recommend audit opinion) are, unsurprisingly, used less frequently (i.e., means below the midpoint of the scale). As one would expect, DDAs are used most frequently by large audit firms. Interestingly,

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[20] Audit education in Denmark is aligned with the International Federation of Accountant's International Education Standards (IES).
[21] Egholm (2022) identifies more than 30 other international networks with Danish members, such as a.o. GGI, Praxity, Nexia, and Kreston.
[22] This large market share can be explained by the Danish professional auditors association FSR—Danske Revisorer's 2014 purchase of Caseware's Danish distribution rights. FSR closely cooperated with Caseware on customizing the software to Danish needs. It was sold back in December 2021 to CWI, who now operates it through CWI Denmark (e.g., FSR 2021; Caseware 2023). The standard user interface is in English, whereas customized modules will mostly be locally programmed in Danish.

APPENDIX A (continued)

TABLE A3

Use of Different Types of DDAs

	Mean					
		Seniority		***Firm size***		
Question Scale Items	**Overall**	**High**	**Low**	**Large**	**Medium**	**Small**
How often do you use the following DDAs during assurance engagements? *Responses were captured on a scale from 1 ((nearly) never) to 5 (very often)*						
Electronic help files	3.9644	3.9886	3.8947	4.1084	3.8868	3.7980
Electronic questionnaires and/or checklists	4.0814	4.1758	3.8092	4.1364	3.8679	4.1162
Digital tools that help assess client acceptability and/or independence	4.0305	4.0890	3.8618	4.0909	4.0377	3.9394
Digital tools that help assess whether specialists should be involved	2.7946	2.8307	2.6908	3.0000	2.3679	2.7259
Digital materiality calculators	4.1732	4.1876	4.1316	4.1399	4.1698	4.2234
Digital test sample calculators	3.1868	3.1716	3.2303	3.9161	2.4623	2.5178
Data analysis tools (e.g., used to extract and analyze data)	2.9966	2.9817	3.0395	3.5804	2.4151	2.4619
Digital templates for audit strategies	3.7177	3.8073	3.4605	3.8702	3.6509	3.5330
Digital tools that recommend specific audit strategies	3.4303	3.4977	3.2368	3.5544	3.3302	3.3046
Digital tools that indicate relevant risks	3.4133	3.4633	3.2697	3.5614	3.1226	3.3553
Digital tools that identify control objectives and recommend respective testing of internal controls	3.0034	3.0137	2.9737	3.2308	2.7170	2.8274
Digital tools that help assess the effectiveness of internal controls	2.6299	2.6110	2.6842	2.9056	2.2170	2.4518
Digital tools that recommend substantive testing, such as transaction testing	3.0628	3.0732	3.0329	3.3077	2.6887	2.9086
Digital tools that check the completeness of working papers and information	3.2211	3.2936	3.0132	3.3684	3.0943	3.0761
Digital tools that recommend audit opinion	2.5340	2.5183	2.5789	2.6281	2.2642	2.5431
DDA Usage[a]	3.3497	3.3807	3.2605	3.5616	3.0862	3.1848

[a] "DDA Usage" is the summative scale of all previous items of Table A3. Cronbach's alpha for the summative scale is 0.8978, indicating a very good level of reliability.

Variable Definitions:
Seniority = defined as described in the notes to Table 3; and
Firm size = "Large" refers to the Big 4 plus the next eight largest Danish audit firms. "Medium" refers to firms more than five partners (but not those mentioned before). "Small" refers to the remainder (see also Table A1, Panel A, which uses a similar categorization).

our results suggest that auditors' use of DDAs is fairly similar in medium and small firms and is still considerable.[23] Our results indicate that auditors with high- and low-seniority indicate a comparable usage of the different types of DDAs. Figure A1 presents a visualization of results for the overall sample. The stacked bar chart outlines the distribution of responses in detail. Only a very small percentage of participants indicate (nearly) no use of the different types of DDAs. Only two participants responded with "(nearly) never" to all provided DDAs (untabulated).[24] Our results are in line with a 2019 survey on digitalization readiness in the Danish audit profession (Liempd et al. 2020) but suggest use of DDAs has further increased since then. In summary, presented results suggest the vast majority of our participants, across different hierarchical levels and firm sizes, have at least some experiences with different types of DDAs and are well equipped to provide insights on matters of interest in this study. Furthermore, with the Danish institutional landscape and auditing regulations reflecting the profession's global requirements, our findings should generalize to other European and U.S. jurisdictions.

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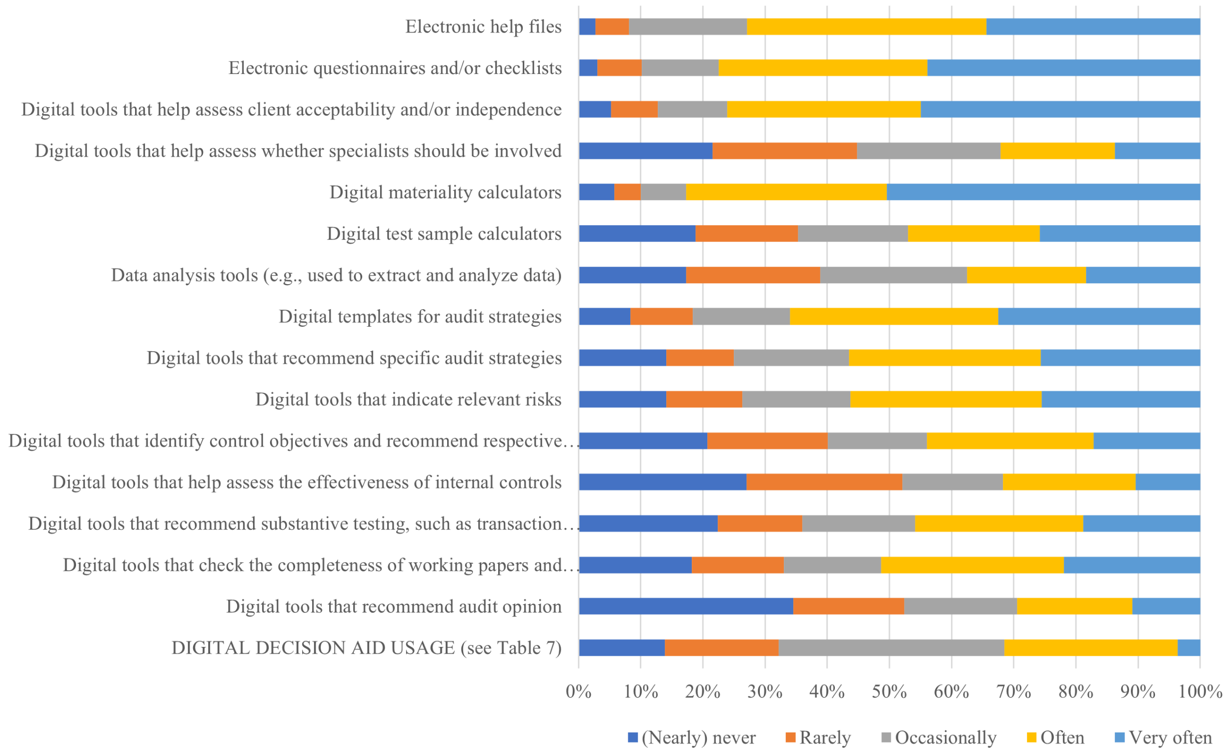
[23] A 2021 survey of 133 Danish certified auditors shows that most use DDAs, including 93 percent who use them for data analytics (Seismonaut 2021).
[24] We left these observations in our sample for all analyses. Dropping them does not change the results.

APPENDIX A (continued)

FIGURE A1
Use of Different Types of DDAs by Survey Participants



(The full-color version is available online.)