Exploring the Impact of Technology Dominance on Audit Professionalism through Data Analytic-Driven Healthcare Audits

Jared Koreff  
*Trinity University*

Lisa Baudot  
*École des hautes études commerciales de Paris*

Steve G. Sutton  
*NHH Norwegian School of Economics*

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Exploring the Impact of Technology Dominance on Audit Professionalism through Data Analytic-Driven Healthcare Audits

Jared Koreff
Trinity University

Lisa Baudot
HEC Paris

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

ABSTRACT: Artificial intelligence (AI)-enabled tools and analytics hold the potential to radically alter audit processes by disseminating centralized audit expertise. We examine this potential in the context of data analytic-driven audits mandated to reduce fraud, waste, and abuse in a government-sponsored healthcare program. To do so, we draw on semistructured interviews with healthcare providers (i.e., auditees) subject to healthcare audits. Our work shows how use of paraprofessional auditors guided by AI-enabled tools and analytics reflects a very different audit environment. Specifically, auditees’ experiences suggest paraprofessional auditors lack specific expertise and credentials to conduct data-driven audits, apply judgment in deference to technology, and disregard the impact of AI-driven decisions on the public interest. Such experiences raise potential concerns for all audits over unbridled use of AI-enabled tools and analytics by novice-level auditors/paraprofessionals, but even more for audits conducted in contexts where adherence to professional norms is essential to minimizing public interest consequences.

JEL Classifications: M42; M48.

Keywords: AI-enabled audit; technology dominance; professionalism; data analytics; healthcare.

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Jared Koreff, Trinity University, Michael F. Neidorff School of Business, School of Accounting, San Antonio, TX, USA; Lisa Baudot, HEC Paris, Department of Accounting and Management Control, Jouy-en-Josas, France; Steve G. Sutton, NHH Norwegian School of Economics, Department of Accounting, Auditing, and Law, Bergen, Norway and University of Central Florida, Kenneth G. Dixon, College of Business Administration, School of Accounting, Orlando, FL, USA.

Supplemental material is available, as linked in the text.

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I. INTRODUCTION

Advances in technology enable compilation of digital records (Power 2021) and larger data sets at exponential rates, creating opportunities to develop and apply novel types of analytics to these data (Brown-Liburd, Issa, and Lombardi 2015). The expansion of artificial intelligence (AI)-enabled tools and analytics is viewed as necessary for the future of auditing, yet firms and regulators alike continue to express concerns regarding implementation of these tools (Eilifsen, Kinserdal, Messier, and McKee 2020; Austin, Carpenter, Christ, and Nielson 2021; Public Company Accounting Oversight Board (PCAOB) 2021). Many open questions remain regarding AI-enabled tools and analytics in audit contexts (Dowling and Leech 2014), including dilemmas associated with displacing knowledge workers and whether and when the use of technology provides more effective solutions (Sutton, Arnold, and Holt 2018; Strich, Mayer, and Fiedler 2021). Whereas extant literature focuses on conceptualizing and problematizing data analytic-driven audits carried out by public accountants (Salijeni, Samsonova-Taddei, and Turley 2019, 2021; Austin et al. 2021), there are limited opportunities to directly examine AI-enabled tools and analytics in such audits. As such, we turn to the public sector context with a broad objective to examine an instantiation of AI-enabled tools and analytics employed in government-mandated healthcare audits. This unique type of audit investigates alleged fraud, waste, and abuse in the public healthcare system in the U.S.¹

The government-mandated healthcare audits serving as our empirical exemplar emerged from legislation in the U.S. requiring the Centers for Medicare and Medicaid Services (CMS) to design and implement an AI-enabled tool and data analytics that identify high-risk healthcare claims to prevent and reduce fraud, waste, and abuse in government-sponsored healthcare. Subsequent to the AI-enabled tool identifying high-risk claims, a contracted audit firm (not a public accounting firm) conducts an audit of the healthcare provider submitting the claims. The audit firm analyzes data related to services with unusual patterns of claims, using their professional judgment to determine the depth and breadth of appropriate audit procedures while adhering to U.S. generally accepted auditing standards (GAAS) and U.S. generally accepted governmental auditing standards (GAGAS, commonly referred to as the Yellow Book) (Centers for Medicare and Medicaid Services (CMS) 2007).² Reports to Congress describe the use of healthcare audit data analytics (H-ADA) as highly successful, touting significant and increasing returns on investment (ROI) to the government (Department of Health and Human Services (DHHS) 2012, 2014, 2015). Other reports identify that ROI calculations are inflated, such as having “included invalid assumptions that may have affected the accuracy” (DHHS 2012). Not only is ROI inflated, but levied fines and penalties are commonly appealed or litigated, with 80 percent of initially levied fines and penalties not collected (Office of Inspector General (OIG) 2017). Further, a review of practitioner articles challenges the success of the healthcare audit mandate from the standpoint of the healthcare providers themselves (Vishnevetsky 2012; van Halem, Nelson, Colbert, and Nienberg 2012; Baucus, Hatch, Grassley, Carper, and Wyden 2013). This led us to question what we can learn about the application of AI-enabled tools and analytics within a public sector healthcare audit context.

We draw on 36 semistructured interviews with healthcare providers subject to the H-ADA to examine our research question. We situate our study in the literature on emerging audit technologies and their impact on audit processes and outcomes. A growing body of literature suggests that structured audit techniques, such as AI-enabled tools and analytics, are increasingly used to guide novice auditors through processes they are not otherwise skilled at conducting (Dowling and Leech 2014; Sutton et al. 2018). These tools and analytics may provide novice auditors with a greater sense of expertise and higher confidence in their performance (Dowling and Leech 2014) and are promoted as reducing subjectivity in professional judgment (Dowling, Knechel, and Moroney 2018; Boland, Daugherty, and Dickins 2019). They also enable shifts in professional work from traditional auditors to paraprofessionals (R. Susskind and D. Susskind 2015; Sutton et al. 2018), which some see as benefitting society by making professional expertise more accessible and affordable (Susskind and Susskind 2015). At the same time, AI-enabled tools and analytics, and their use by paraprofessionals, transform commonly accepted audit processes and outcomes (Robson, Humphrey, Khalifa, and Jones 2007). We propose to understand such transformations through the eyes of auditees undergoing AI-enabled healthcare audits.

Overall, our findings suggest that, from the perspective of auditees, AI-enabled tools and analytics enable the contracted auditors to transform audit processes and outcomes with much less regard to traditional professional norms. Auditees perceive the auditors as paraprofessionals lacking appropriate professional expertise and credentials, including knowledge of the structured audit techniques they employ. The auditees also express that the contracted auditors create distance in and immobilize auditee interaction in the audit process but do so by deferring to the output of AI-enabled

¹ See the Online Appendix for a general comparison of the related audit activities with those associated with public sector financial statement audits and public sector single audits by CPAs in the U.S. context.
² See Section 4.7.3 in the statement of work.
tools and analytics to dictate audit judgments and justify audit outcomes without regard for potential false positives. Furthermore, the auditees suggest that without appropriate knowledge, expertise, and professional judgment, the contracted auditor’s use of AI and analytics can encourage outcomes detrimental to the public interest. When discussing their experiences subject to H-ADA, auditees organically highlight trends that violate traditional professional norms and expectations and proceed to delegitimate the healthcare auditors on this basis. Although reflecting a potentially defensive construction on the part of the auditees, their perceptions nevertheless raise concerns for the (mis)application of analytics in the performance of government-mandated healthcare audits. These perceptions also question the shift of data analytic-driven audit work to less experienced auditors and/or paraprofessionals who may not operate in accordance with professional norms, particularly in the public sector audit context, where those norms may be even more critical when considering the public interest implications.

Our work makes several contributions to the literature on the use of AI-enabled tools and analytics in audits and auditor activities in both the public sector audit context we study and more broadly. First, we contribute to the nascent literature on technological transformations resulting from investments in audit data analytic tools (Austin et al. 2021) and their increased use in the audit process (American Institute of Certified Public Accountants [AICPA] 2017; Appelbaum, Kogan, and Vasarhelyi 2017; Boland et al. 2019). Whereas this literature often focuses on experimental examinations of AI applied to various auditor judgments and decisions (e.g., Barr-Pulliam, Brazel, McCallen, and Walker 2023; Commerford, Dennis, Joe, and Ulla 2022; Koreff 2022), our study presents field experiences of actual use of AI-enabled tools and analytics in an audit process and their potential hazards and pitfalls. Prior research shows how AI-enabled tools and analytics may dictate audit performance in place of auditor expertise and judgment (Arnold and Sutton 1998; Brown-Liburd et al. 2015; Sutton et al. 2018, 2023), which raises concerns about AI use in regulatory or enforcement processes (Williams 2013). In our case, an AI-enabled tool and analytics promote auditor myopia in searching for evidence to support an automated conclusion seemingly due to overreliance on simple heuristic-based systems absent an understanding of the context of the anomaly detected. This is consistent with a form of technology dominance generally referred to as automation bias—the instinctive need to react to a system-identified concern without considering the context (Skitka, Mosier, and Burdick 1999; Sutton et al. 2023). Important public interest consequences emerge from technology producing outputs and auditors not having (or appropriately using) the professional expertise and judgment to interpret analytically identified risks, execute relevant audit procedures, and draw sound conclusions from the outputs. In the context of healthcare audits, where access to government-sponsored healthcare is at stake, the human, and particularly the professional judgment, element remains critical to the proper functioning of audits (Sutton et al. 2018).

Second, we contribute to the literature on auditees’ perspectives (Power 2003; Gendron, Cooper, and Townley 2007; Daoust and Malsch 2019, 2020), specifically in relation to how AI-enabled tools and analytics may transform audit processes, outcomes, and professionals (Austin et al. 2021). Prior research focuses on the auditor perspective of how AI-enabled tools impact audit processes, auditor work, and decision-making (Salijeni et al. 2019, 2021). In the context of AI-enabled tools and data analytic-driven healthcare audits, we find a scenario in which auditees have little influence on audit outcomes as auditors exhibit a clear adherence to the prescriptions of tools and analytics. In such scenarios, auditees reconcile exclusion from auditors’ work and decision processes, particularly when “wrongly accused,” by delegitimizing paraprofessional auditors’ interactions with the technology relative to the auditees’ understandings of professional norms. This not only represents a departure from the idea that auditees play an influential role in audit processes (Guénin-Paracini, Malsch, and Tremblay 2015; Daoust and Malsch 2020) but suggests that technology acts as an intermediary/barrier between the auditor and auditee, rather than a bridge (Salijeni et al. 2019, 2021).

Finally, our work on auditees’ experiences of data analytic-driven audits performed by paraprofessionals contributes to our understanding of the consequences of technology dominance, and concomitant exclusion of professional judgment, for audit processes (Arnold and Sutton 1998; Sutton et al. 2023). Regarding notions of audits and audit professionals, during a time of continued technological advancements, our work suggests that such notions represent taken-for-granted models inspiring professional norms for administrative procedures and reforms (Pentland 2000; Susskind and Susskind 2015). The applicability of conventional professional markers and their transferability, facilitated (or inhibited) by AI-enabled tools, to public sector healthcare audits are important questions (Andon, Free, and Sivabalan 2014; Andon, Free, and O’Dwyer 2015; Susskind and Susskind 2015), particularly as seemingly knowledge-based needs expand. As Radcliffe, Cooper, and Robson (1994, 606) state: “the idea that auditors are professionals, and that accountability work is professionalized is not an immutable fact but open to dispute and contestation.” Indeed, our work suggests heightened concerns regarding paraprofessionals leveraging AI-enabled tools and analytics who seemingly lack the innate attributes of their professional peers and therefore may sidestep professional norms despite the public sector context being one where idealized audits and auditors serve an important role in protecting the public interest. Overall, the results provide initial evidence supporting the impact of using AI-enabled tools on deprofessionalization of professional work (Susskind and Susskind 2015; Sutton et al. 2023).
II. RELEVANT LITERATURE

Recent years have seen a rise in the range and sophistication of AI-enabled tools and analytics, including artificial intelligence, machine learning, and process mining (Jans, Alles, and Vasarhelyi 2013, 2014; Sutton et al. 2018; Jans 2019). Public accounting firms suggest that AI-enabled tools and analytics signal competitive advantage (Carson and Dowling 2012) and promote effective and efficient audits (Dowling 2009). However, AI-enabled tools and analytics remain underutilized in financial statement audits (Austin et al. 2021), with their acceptance stymied by audit firms and regulators alike (Elifßen et al. 2020; Austin et al. 2021). As AI-enabled tools and analytics advance, they are anticipated to transform the audit field as a whole (Robson et al. 2007), including both the professionals and the work they perform (Salijeni et al. 2019, 2021).

From the AI-enabled technologies perspective, changes in auditor professionalism can be viewed as a product of technology dominance (Arnold and Sutton 1998; Sutton et al. 2023). The theory of technology dominance (TTD) focuses on the strong influence of AI-enabled tools on different expertise levels of professional knowledge workers and the transformational effects on professions. Key to our study is the technology dominance that is expected to occur with novices (e.g. paraprofessionals) who are ill prepared to complete the task at hand without the tool.3 Of additional interest are the extensions in TTD2 (Sutton et al. 2023) related to the potential deleterious effects of AI-enabled technologies on the foundation and evolution of knowledge work professions, such as auditing.

TTD posits that knowledge workers (e.g., auditors) are at substantial risk of poorer decision-making when there is a mismatch between the expertise embedded in an AI-enabled technology and the expertise of the user. Novice-level decision makers (e.g., junior professionals or paraprofessionals) are unable to recognize when AI-enabled tools are out of their domain of expertise, while at the same time generally possessing a strong propensity to overly rely on AI-based system output (Arnold and Sutton 1998). TTD2 expands upon these concerns to provide a theoretical understanding for why such phenomena occur. TTD2 posits that novices’ decisions become more biased from overreacting to system outputs, novices are more task completion-focused than judgment-focused, novices use more surface-level than deep knowledge structures when forming decisions, and novices become overconfident in their decisions through a miscalibration of their own knowledge in the decision domain (Sutton et al. 2023).

TTD2 also explores how AI-enabled technologies begin to erode the foundations of knowledge work professions (Sutton et al. 2023). The increased use of automation through AI-enabled technologies alleviates the need for more expensive expert decision makers, a practice viewed as key to eroding the mystique and prestige around a profession, potentially leading to deprofessionalization (Susskind and Susskind 2015). Susskind and Susskind (2015) observe an increasing use of paraprofessionals armed with AI-enabled technologies across many professions, including auditing. The paraprofessional model innately understands that a paraprofessional cannot reliably deliver full professional services. But the model also assumes benefits from such a model as paraprofessionals can be boosted by AI-enabled tools that allow professional services to be provided at a much lower cost and without barriers from shortages of experts in a professional domain (Sutton et al. 2018). Similarly, as a long-term risk of AI-enabled tools that induce technology dominance, Sutton et al. (2023) link the increasing use of novices in leveraging AI-enabled tools to the deprofessionalization of professional knowledge work, such as audit.

Important to the current study is the related philosophy and theory of professions that is at the heart of the projections put forth by Susskind and Susskind (2015) and Sutton et al. (2023). Most theories of the professions revolve around structures that are thought to create and validate expertise in a domain that is important to the public interest and requires a unique and difficult to attain knowledgebase to perform the professional work (Covaleski, Dirsmith, and Rittenberg 2003; Kultgen 1988). To validate the existence of such expertise, professionals are generally credentialed with some form of recognized certification or licensure and expected to continually educate themselves to maintain currency in the domain (Kimball 1995; Kultgen 1988). All of this professional knowledge is expected to be provided by the professional through expert judgment and should be the type of decision-making that is non-programmable, that requires an analysis and interpretation of the information at hand when making key decisions (Gendron et al. 2007). To the degree that paraprofessionals are integrated into professional domains, the mystique of expertise is undermined through the absence of observable and validated knowledge. To the degree AI-enabled technologies are deployed, questions also arise regarding the nonprogrammability of experts’ judgments (Susskind and Susskind 2015; Sutton et al. 2023). These latter concerns present themselves in the current study.

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3 A paraprofessional is “an individual used in place of a professional to perform tasks for which the full range of professional experience is not required; an individual classified by the scope of his or her education and/or training, which might encompass only a small portion of the full range required for professional status; an individual characterized by the absence of a license to practice or other formally recognized status” (Hicks and Rymer 1990, 84).
Technology, Analytics, and Audit Professionals

Most audit research examines audit through the lens of public accounting professionals (Daoust and Malsch 2019, 2020). The conventional argument is that such professionals provide higher quality service owing to their procedural and methodological expertise alongside recognized and ingrained ethical and behavioral characteristics of the profession (Wyatt 2004). However, over the past few decades, it has become commonplace, especially for the largest accounting firms, to contract out lower-level accounting and auditing tasks that better lend themselves to objective solutions and automation (Lyubimov, Arnold, and Sutton 2013; Susskind and Susskind 2015) as well as to use robotic process automation (RPA) tools (Eulerich, Pawlowski, Waddoups, and Wood 2022). At the other end of the spectrum, as accounting issues grow more complex, more and more subject matter experts (e.g., data science, information systems, valuation), who are less likely to have professional backgrounds in accounting and auditing, are also engaged in provision of audit services (Eilifsen et al. 2020). Recent trends suggest that data scientists and information systems specialists now perform certain data analytic tasks more frequently than more traditional audit team members (Eilifsen et al. 2020).

Taken together, these trends have the effect of shifting audit work to paraprofessionals (Hicks and Rymer 1990), yet the use of paraprofessionals in audits is not new (Loeb and Rymer 1973) and is suggested to decrease costs in light of increased competition and/or mitigate the adverse impacts of a limited supply of available professionals (Susskind and Susskind 2015). Indeed, from the late 20th century, practitioners proposed that much of the work involving routine, detailed, repetitive tasks could be handled by novice-level paraprofessionals teamed with AI-enabled technologies to improve productivity in audit processes (Nelson 1989; Susskind and Susskind 2015; Arnold and Sutton 1998).

Other audit contexts, such as the public sector (Radcliffe 1998, 1999, 2008), illustrate a “family resemblance” to aspects of financial statement audit (Pentland 2000, 307), yet those same contexts lend to the mobilization of paraprofessionals with specialized, non-accounting, or non-auditing expertise to collect, analyze, and interpret evidence and communicate findings. Such paraprofessionals may acquire different understandings of procedural, ethical, and behavioral conduct (Suddaby, Gendron, and Lam 2009; Susskind and Susskind 2015) and develop different embodiments of control, transparency, and accountability (Gendron, Cooper, and Townley 2001; Gendron et al. 2007) compared to public accounting professionals. For instance, public accountants are suggested to be more committed to the ethics of their profession than those in other audit contexts and with different backgrounds (Suddaby et al. 2009). As ethical norms and standards are intertwined with the culture of public accounting firms (Anderson-Gough, Grey, and Robson 2000; Grey 1998; Pentland 1993), traditional accounting professionals gain exposure to (and are socialized to engage with) norms and standards that paraprofessionals do not. Paraprofessionals may not be exposed to these same behavioral expectations in conducting audits and, thus, may perform audits in significantly different ways, with reference to varying professional ethics and norms (Suddaby and Greenwood 2001; Susskind and Susskind 2015), and influenced more by the structured audit techniques in AI-enabled tools (Dowling et al. 2018; Boland et al. 2019; Sutton et al. 2018).

All of this suggests that trends shifting audit tasks toward AI-enabled tools and analytics become even more critical to understand when employing paraprofessionals. Advances in AI-enabled tools and analytics can not only displace lower-level professional work, tasks, and processes (Sutton et al. 2018; Gunz and Thorne 2020; Munoko, Brown-Liburd, and Vasarhelyi 2020) but also enable paraprofessionals to perform tasks and processes they might otherwise be unable to complete (Arnold and Sutton 1998; Dowling and Leech 2014; Susskind and Susskind 2015; Sutton et al. 2023). In completing these tasks and processes, paraprofessionals may see the technology as an immutable authority to which decision-making responsibility is safely abdicated (Gunz and Thorne 2020; Sutton et al. 2023). Auditors’ use of AI-enabled tools and analytics may impact their professional judgment by structuring tasks and diseminating expertise, encouraging compliance with the tool (Dowling et al. 2018; Boland et al. 2019). Even where auditors may react defensively to compliance-oriented tools (Dowling et al. 2018), these tools encourage the standardization of audit processes, providing a sense of comfort to auditors, firms, and regulators (Dowling and Leech 2014; Boland et al. 2019). As Dowling and Leech (2014) suggest, AI-enabled tools may reduce auditor uncertainty and provide a kind of “safety net” for defending outcomes.

On this point, auditors suggest AI-enabled tools and analytics play a role in resolving disagreements with auditees, specifically in areas involving a significant amount of judgment, where data analytic evidence used to support auditor conclusions is perceived as “facts” holding greater weight (Saljijeni et al. 2019). Overreliance on these “facts,” however, may lead auditors to fail to consider factors or risks not explicitly identified by AI-enabled tools (Seow 2011) or to insufficiently evaluate the conclusions reached by the tool (Glover, Prawitt, and Spilker 1997). Ultimately, such overreliance on AI-enabled tools and analytics may not only reduce auditors’ ability to exercise professional judgment (Dowling and Leech 2014), but also make audits less susceptible to auditee attempts to influence audit outcomes.

Although auditees are acknowledged to have influence over the way that auditors perform audits (Anderson-Gough et al. 2000; Guénin-Paracini et al. 2015; Daoust and Malsch 2020), this influence might be experienced differently when
AI-enabled tools and analytics are involved. From the auditor’s perspective, auditees experience data analytic-driven audits positively (Salijeni et al. 2019, 2021). Indeed, public accounting firms promote their investments in and use of AI-enabled tools and analytics from a value-added standpoint in terms of the opportunities they create to communicate business process and operational improvements (Austin et al. 2021). At the same time, Austin et al. (2021) acknowledge how auditees are sometimes at the root of difficulties in implementing tools and analytics in the audit process. Overall, auditees’ experiences are not well documented in the prior literature (Guénin-Paracini et al. 2015; Daoust and Malsch 2020), including their perspective regarding the implementation and use of AI-enabled tools and analytics in audit practice (Salijeni et al. 2019, 2021). We ask what we can learn about the application of AI-enabled tools and data analytics within a public sector healthcare audit context through the experiences of auditees.

III. RESEARCH FIELD AND METHOD

Our research questions are relevant to understanding AI-enabled tools within the public sector healthcare context. Public sector audits provide policy makers with opinions on whether government activities achieve an intended outcome (Chelimsky 1985). Such audits often report on waste, inefficiency, and abuse of public resources in government programs (Power 1997, 1999; Gendron et al. 2001). With this focus, public sector audits suggest a mentality toward uncovering and sanctioning noncompliance and illegitimate or fraudulent conduct (Gray 2008).

The auditors of concern in this study are expected to perform as audit professionals within the scope of the defined attestation domain. Although the healthcare auditors do not generate the output of the AI-enabled technology, the embedded data analytics resemble those that would normally be used in many different audit contexts (see Figure 1).4 In Section 4.7.3 of the Statement of Work that specifies the expectations of the healthcare auditors from CMS, the auditors are specifically tasked with gathering the necessary evidence to analyze whether claims are irregularities or fraudulent activities associated with particular services or groups of services with unusual growth, particular providers or beneficiary demographics, new services provided to patients, and other unusual patterns. The auditors are to apply their judgment to the breadth and depth of evidence examined and are required to follow GAAS and GAGAS appropriately (CMS 2007) (see also the Online Appendix for additional description).5

As an important empirical context with a certain resemblance to other audit scenarios, we use the healthcare audit to explore concerns around the use of AI-enabled tools and analytics in conducting an audit. To do so, we conducted a qualitative field study, which is preferable in examining nascent and unexplored phenomena (Sutton, Reinking, and Arnold 2011; Power and Gendron 2015). Auditees’ experiences undergoing AI-enabled, data analytic-driven healthcare audits in the public sector context constitute an example of such phenomena.

Field of Investigation

The U.S. government has long considered healthcare programs administered by CMS within the Department of Health and Human Services (DHHS) as high risk for fraud, waste, abuse, and mismanagement (Department of Health and Human Services (DHHS) and Department of Justice (DOJ) 1998). In this regard, Section 4241 of the U.S. Small Business Jobs Act of 2010 (SBJA) mandated CMS to implement an AI-enabled, data analytic tool to ensure the accuracy of payments made to healthcare providers for services covered under government-sponsored healthcare programs (Centers for Medicare and Medicaid Services (CMS) 2018a). In response, CMS created the Center for Program Integrity (CPI) to protect government programs against losses from fraud, abuse, and improper payments and to improve the integrity of the healthcare system (Centers for Medicare and Medicaid Services (CMS) 2013). The CPI then implemented an AI-enabled fraud prevention system to identify potentially fraudulent claims.

Since June 2011 (DHHS 2012), the fraud prevention system has captured and stored healthcare data and used algorithms and models (i.e., H-ADA) to detect high-risk, unusual, or suspect claims made by healthcare providers.6 The algorithms and models identify high-risk outliers using rules, anomaly-, predictive-, and network-based H-ADA (see

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4 For example, it is common in audit firm environments for the data analytics to be run by data scientists and the outputs provided to the audit team to develop an audit plan and associated testing procedures that investigate identified high-risk areas (Ellifsen et al. 2020).
5 Section 4.7.3 of the Zone Program Integrity Contractors (ZPICs) Statement of Work from CMS includes the following language for the types of analysis that may be performed (CMS 2007): “Types of data analysis performed may include:Analyzing data for a particular service or group of services that appear to be experiencing unusual growth in utilization; analyzing data for a specific time frame; analyzing data for a particular provider or beneficiary demographic; examining utilization patterns and trends for newly covered services; determining if a particular claims system edit is having the intended effect; performing and validating new types of analysis or experimental analysis; and other analysis as may be identified by the ZPIC(s).”
6 Within the healthcare industry in the U.S., revenue is generated by healthcare providers rendering services, and then potential payers, such as insurance companies or government programs, are billed so that the healthcare provider can be reimbursed for services rendered.
Figure 1). On this basis, the H-ADA flags activities such as high numbers of referrals between providers, referrals from high-risk physicians, treatment of high-risk patients, excessively long treatment periods, unexpectedly low or high expenses, and rapid provider revenue growth. Important to recognize is that claims made by the healthcare providers that are identified by the H-ADA represent unusual and potentially fraudulent claims—the H-ADA models are intended to identify the level of fraud risk.

CMS outsourced responsibility for conducting the audits of potentially fraudulent healthcare claims identified by the H-ADA to four contracted firms (CMS 2007). When providers are identified as high risk using the H-ADA, CPI refers the audit to the contracted audit firm for that zone of the country. Subsequent to the H-ADA identifying high-risk claims, the contracted firm receives analytic outputs regarding claims comprising the different algorithmic models. The firm initiates an audit by targeting a specific risk related to healthcare claims but is granted a broader mandate to investigate the healthcare provider for any overall patterns of irregularities or potentially fraudulent claims (DHHS 2012).

Data Collection

We first reviewed archival and press documents available through CMS’s website (e.g., Reports to Congress, the ZPIC Statement of Work, etc.) and practitioner websites (e.g., articles published by attorneys, CPAs, and consultants). We later obtained additional archival documents from nonpublic sources through Freedom of Information Act (FOIA) requests and other private sources (e.g., emails with attorneys, including associated court documents). These documents establish our understanding of the field of investigation and our research objective to focus on the auditee experience of...

FIGURE 1

Data Analytic Models Used by CMS in H-ADA

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Model Focus/Goal</th>
<th>Medicare Example</th>
<th>Target</th>
<th>Number of Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rules-Based</td>
<td>Filter fraudulent claims and behaviors with rules</td>
<td>Bill for a Medicare identification number that was previously stolen and used improperly</td>
<td>Patients</td>
<td>Rule – 11</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A provider that bills for more services in a single day than the number of services that 99% of similar providers bill in a single day</td>
<td>Provider</td>
<td>Rule – Distance – 2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Provider that has characteristics similar to those of known bad actors</td>
<td>Provider</td>
<td>Rule Based - 17</td>
</tr>
<tr>
<td></td>
<td>Detect individual and aggregated abnormal patterns versus peer group</td>
<td>A provider that is linked to known bad actors through address or phone number</td>
<td>Provider associated with questionable physicians</td>
<td>Anomaly – 30</td>
</tr>
<tr>
<td>Predictive</td>
<td>Assess against known fraud cases</td>
<td>A provider that is linked to known bad actors through address or phone number</td>
<td>Provider associated with questionable physicians</td>
<td>Anomaly analysis – 16</td>
</tr>
<tr>
<td>Network</td>
<td>Discover knowledge with associative link analysis</td>
<td>A provider that is linked to known bad actors through address or phone number</td>
<td>Provider associated with questionable physicians</td>
<td>Social Network Analysis - 4</td>
</tr>
</tbody>
</table>

Adapted from DHHS (2014, 4).

7 The audit contractors are called Zone Program Integrity Contractors (ZPICs). Based on a review of the ZPIC firms’ websites, these firms all promote their services as centered on information technology (IT), insurance, and healthcare services in the government sector. Among their capabilities, the contracted firms include audits, compliance, data analysis, and fraud review.

8 The Freedom of Information Act (FOIA) provides that any person has the right to request access to federal government records or information except where protected by exemption within the act. The research team began seeking additional information from CMS through the FOIA process during our interviews. The process can be tedious, and generally about three rounds of requests were necessary before CMS was willing to provide the requested information. Our FOIA requests spanning July 2016 to October 2018 eventually allowed us to gather nonpublic information related to contractor compensation contracts, written policy and procedures for audit performance, and information related to the nature of the various data analytic models used by CMS.
audits driven by AI-enabled tools and analytics. Although not our primary source data, the archival documents help validate our analysis through triangulation with our interview data (Yin 2009).

We developed a semistructured interview protocol based on our healthcare audit knowledge and what we learned from the archival documents about healthcare audits, refining the protocol in consultation with three accounting practitioners specialized in the healthcare industry.9 Our focus on auditee experiences necessitated contact with healthcare providers subject to audit.10 We initiated interviews with eight healthcare providers obtained through one convenience contact.11 Based on these initial interviews, we then continued with a combination of snowball and theoretical sampling through contacts with trade associations, attorneys, CPAs, and consultants. We conducted a total of 36 interviews.12

The participants work in six different healthcare subindustries, with a significant number from subindustries identified to be high risk.13 Most of the participants were owners and top-managers of healthcare providers. The remaining participants either oversaw or had key insight into claims reimbursement for providers of significant size and capacity.14 In identifying interview participants, we focused on talking with the individuals that had the most interaction with the healthcare auditors. Further, we interviewed participants located in six of the seven geographic zones, covering audits by three of the four contract firms.15 Overall, there is substantial diversity among participants; however, we did not identify significant differences in audit experiences attributable to different subgroups (i.e., provider type, region, or firm). Table 1 provides demographic information.

The interviews took place in person or by phone based on the participant’s preference with no notable difference in the content or the extent to which participants were candid and forthcoming about their experiences. Formal interviews lasted from 31 to 104 minutes (48 minutes on average) and occurred between March 2015 and April 2017. All formal interviews except one were recorded. During this interview, the researcher took extensive notes and wrote direct quotes when possible. We also prepared detailed notes during and after each interview and reflected on the topics covered in the interview. One researcher transcribed all recorded interviews. Informal interviews with several participants continued through March 2022, to monitor any changes in the audit environment, but these informal data did not provide any noteworthy new insights.16

Data Analysis

During our reflection on the interviews, we continually reviewed our understanding of the role of AI-enabled tools and analytics in the audit, how the auditors employed these tools and analytics, and how auditees experienced the data analytic-driven audit. With these questions in mind, we conducted open coding on our interviews to identify recurring themes (Yin 2009). In our initial round of open coding, we identified that auditees consistently discussed the following themes in their experience as healthcare auditees undergoing AI-enabled, data analytic-driven audits: auditors’ backgrounds and credentials; auditors’ knowledge and use of technology; auditors’ decisions around evidence collection; auditors’ documentation, report findings, and communications with auditees; and the societal impacts of data analytic-driven

9 The institutional review board (IRB) at the researchers’ university determined the research exempt.
10 Prior research consistently focuses on interviews only with auditors and to a limited extent only with auditees. We did consider pursuing reactions from the healthcare auditors. To contact auditors, one co-author attended conferences/webinars where senior healthcare auditors from the contracted audit firms spoke. The auditors emphasized the magnitude of fraud in government-sponsored healthcare, including how COVID and passage of related legislation had increased the prevalence of healthcare fraud, creating an even greater need for AI-driven healthcare audits. This led us to conclude that auditors may be unlikely (or unwilling) to reflect on the potential weaknesses in the process or implications of the H-ADA outside of what we already acknowledge to be their important role in preventing actual frauds.
11 Whereas it is possible that our contact connected us with people having a consistent view, we did not discuss the focus of our study when soliciting participants (other than a desire to understand the audit process). Furthermore, regardless of how we gained access to participants, the common themes emerging from the interactions that took place provide us with comfort that we reached appropriate people in key positions within the healthcare provider organizations and that those people were candid about their experiences undergoing the healthcare audit.
12 None of the researchers had a pre-existing relationship with any of the participants or organizations in this study.
13 The home health industry is considered at high risk of fraud, waste, and abuse (Office of Inspector General (OIG) 2016; Department of Health and Human Services (DHHS) and Department of Justice (DOJ) 2019); thus, it is not surprising that home health providers are targeted by the H-ADA and compose an important part of our sample.
14 It is important to note that no participants in our sample were found guilty of healthcare fraud. Even where participants in this study incurred fines, none were fraud-related. All fines reported in participants in this study were attributable to alleged insufficient documentation. The participants not being found to commit healthcare fraud does not diminish their experience in undergoing a healthcare fraud audit. Rather, this helps to validate the perceptions of auditees as common experiences as opposed to capturing cases of fraud that may introduce volatility into our analysis. However, future research may seek to understand the experience of those convicted of healthcare fraud.
15 We have no reason to believe that individuals in the one geographic region and the one ZIPC firm not covered by the study would experience healthcare audits differently from the individuals in our sample.
16 Subsequent to the conclusion of the formal interviews, we did attempt to talk to auditees who had actually committed fraud (as opposed to the documentation irregularities found in the vast majority of audits). We went through the process of getting IRB approval to talk to prisoners, and after receiving permission, we wrote to numerous prisoners serving time for convictions on Medicare fraud. None of the contacted individuals responded to our requests.
### TABLE 1
Demographic Information of Auditees

<table>
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<th>Participanta</th>
<th>Subindustry</th>
<th>On Site Auditb</th>
<th>Finesc</th>
<th>Hot Spota</th>
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</tr>
</tbody>
</table>

*a* We refer to participants as “Oper” when their job titles/positions place them in operational roles within the healthcare provider (e.g., administrators or directors in care management, compliance, legal, clinical care or services, nursing, operating, revenue management). We refer to participants as “Exec” when their job titles/positions place them in C-suite roles (e.g., CEO, CFO, executive director, owner).

*b* Indicates whether a ZPIC auditor was physically on site at any point during the audit as compared to an audit that was conducted completely at a distance (by email, phone, and electronic means).

*c* Indicates whether fines were imposed on the participant’s employing organization as a result of the ZPIC audit. Where “yes,” all fines were attributable to documentation issues. None were fraud-related.

*d* Provider has at least one location in one of the nine designated fraud hot spots (DHHS 2012).

*e* Durable medical equipment company.

*f* Providers who had consulting or tax work performed by a CPA but not an external audit.

*g* Skilled nursing facility, commonly known as a nursing home.

*h* Provider did not have a ZPIC audit but, rather, spoke based on what they understood to be happening to other providers with whom they interact.
work performed by the auditors. As we read (and reread) the interview transcripts, abstracting the initial codes at a higher level, we recognized professional norms to be prominent in how auditees described their experiences with these audits and the auditors conducting the audits, without prompting on such norms within our interview protocol. Therefore, the development of our analysis was based on grouping initial themes emerging from the transcripts into higher-order categories that referred to professional norms and the use of AI-enabled tools and analytics by auditors conducting healthcare audits. Ultimately, we group aspects of auditees’ experiences into three analytical categories indicative of professional norms commonly recognized in scholarship and their relationship to AI-enabled tools and analytics.

First, auditees perceive their healthcare audit experiences relative to auditors’ knowledge and expertise (Kultgen 1988; Grey 1998; Covaleski et al. 2003; Susskind and Susskind 2015) of the AI-enabled tool, its output, and the underlying data. Relatedly, auditees evaluate auditors’ knowledge and expertise with reference to the auditors’ backgrounds (Covaleski et al. 2003; Grey 1998; Kimball 1995). Second, auditees present their healthcare audit experience as a function of the auditors’ ability to make appropriate judgments and decisions in relation to data analytic processes and results (Abbott 1988; Larson 1977; Elliott 1999; Kultgen 1988; Susskind and Susskind 2015). Finally, auditees’ experiences undergoing data analytic-driven healthcare audits are understood in relation to audit outcomes, in this context the potential impact that overreliance on technology may have on the continued provision of healthcare services (Kultgen 1988; Fogarty, Radcliffe, and Campbell 2006).

Although established professional frameworks guide these analytical categories, we do not impose any one framework on our empirical material, and we do not seek to judge competing theories of professionalism or professional norms. Therefore, our coding strives to be open to the empirical material and draw organically on auditees’ work on our empirical material, and we do not seek to judge competing theories of professionalism or professional norms. Therefore, our coding strives to be open to the empirical material and draw organically on auditees’ common insights and responses (Kennedy and Thornberg 2018).17 We reached data saturation when additional auditee interviews and analysis neither contradicted nor added any significant new information (Sutton et al. 2011; Malsch and Salterio 2016). We selected the quotes that best represent the main themes identified as exemplars in our analysis.18 The quotes focused on the auditees’ experience in this healthcare audit context and what we can learn about the use of AI-enabled tools and analytics in such audits.

IV. AUDITEE EXPERIENCES OF DATA ANALYTIC-DRIVEN AUDITS

Our analysis demonstrates that auditees speak about their healthcare audit experiences in a way that reflects on data analytic-driven audits, and the auditors who conduct them, relative to professional norms. Although the firms contracted to conduct healthcare audits seemingly employ “professionals” (CMS 2007), auditees do not perceive such auditors to act in accordance with “traditional” professional norms, leading them to delegitimize the audits and the auditors. Auditees consistently raise themes around three professional concerns in relation to AI-enabled tools and analytics, including that audit professionals develop and employ a unique set of knowledge and expertise (Kultgen 1988; Covaleski et al. 2003; Susskind and Susskind 2015), supported by an appropriate signal or credential to certify this expertise (Kultgen 1988; Kimball 1995; Susskind and Susskind 2015); use their unique knowledge and expertise to make judgments that cannot be preprogrammed and to cope with unforeseen problems (Larson 1977; Abbott 1988; Kultgen 1988; Susskind and Susskind 2015); and support the public interest while refraining from self-interested behavior (Kultgen 1988; Fogarty et al. 2006; Susskind and Susskind 2015).

Knowledge, Expertise, and Credentials in Data Analytic-Driven Audits

Auditees discuss their experiences undergoing data analytic-driven healthcare audits in relation to the knowledge and expertise of the auditors. CMS mandates contracted auditors to follow relevant audit procedures and standards, including GAAS and GAGAS (CMS 2007, 94) (see Online Appendix for further elaboration). Whereas auditees do not perceive the healthcare auditors to have adequate knowledge and expertise regarding such standards in conducting their audits, the standards currently speak little to the use of AI-enabled tools and analytics. Still, auditees challenge the auditors’ expertise by questioning the acumen auditors exhibit for what they are auditing based on their backgrounds, whether the auditors understand aspects of the AI-enabled audit process, and the resulting accuracy of the auditors’ assessments of data analytic outputs.

17 Whereas we coded each interview file directly within the transcript, our coding worked similar to the way in which coding works in Nvivo, with the coders keeping a separate list of codes that were referred to in conducting the coding and accumulating coding themes by careful thematic analysis that involved comparison and contrast within and between the transcripts.

18 Several participants requested to approve quotes prior to inclusion and approved all quotes without modification. We also shared earlier drafts of our study with a number of interview participants (Malsch and Salterio 2016).
For instance, auditees indicate that the auditors are not clear on what they are auditing. The participant employed by the most sophisticated provider in our sample explained that when audit documentation is requested, auditees are usually able to comprehend what the auditors are examining and why. However, because this is not the case with the healthcare audit documentation requests, auditees presume that the auditors do not know how to conduct their audit:

I don’t think they know [what they are looking for]. I honestly don’t. I talked to several providers and they all agree [with] me, we don’t think they even know what they were [looking for]. (Exec01)

Once we got that request…we do a clinical review of the charts to look to say “can we figure out what they are looking for, is it anything that looks like it deviates from the norm”…on these particular charts that were pulled…we were grasping to say, “I’m not clear what they are looking for” and there doesn’t seem to be any big deviation. (Oper02)

[They got already close to 50 percent of the charts, if they would base it on my current census, or my yearly census…they already achieved at least 50 percent of that population. That’s more than enough, to say, “okay, does this agency show any evidence of fraud activity? They never told me…that they found fraud.” (Exec19)

Often, auditees present the auditors’ acumen relative to the auditors’ backgrounds and certifications. Professions require extensive training and education (Kultgen 1988; Susskind and Susskind 2015) and a credential certifying formal learning (Kultgen 1988; Kimball 1995; Susskind and Susskind 2015) in a specific domain. By contrast, auditees in our setting convey that the auditors lack training, education, and certification in both auditing and in healthcare expertise with auditees indicating that their auditors were former law enforcement officers rather than auditors.

When they sat down to introduce themselves, none of them had medical backgrounds, they were all law enforcement backgrounds…and each one of them went through their background, had nothing to do with healthcare. (Oper10)

Although the healthcare auditors are encouraged to meet certain education requirements and hold certifications, these remain largely undefined in regulatory guidance (CMS 2007). Furthermore, the contracted audit firms’ policies and procedures do not discuss staffing and qualifications of audit teams, other than referring to the possible need for subject matter experts. In demonstrating concerns related to auditor knowledge and subject matter expertise, auditees call into question the auditors’ understanding of the healthcare industry exemplified as follows:

[We ran background checks on the [healthcare audit] people. One was a disbarred financial planner, one was a CPA that had his CPA license revoked, and the rest of them were all ex-cops, what the hell do they know about healthcare?...so how can you look at clinical charts and evaluate them if you’re not a clinician?” (Exec01)

They also…hire the clinicians to review, but…these ZPIC employees are new, new to the healthcare industry, new to audit....They don’t have the experience like what we have here, over 25 years’ experience....what they hire is just a simple nurse, with less than five years [experience]. (Oper09)

Many auditees took issue that, despite not being physicians, and having a lower level of education than physicians, the auditors “can override a clinician’s determination” (Oper11), largely based on what the AI-enabled tool and analytic output identifies. Taken together, auditees express doubt that the auditors are adequately trained and credentialed in either audit evidence gathering or healthcare, which can hamper the ability of the auditor to interpret and use H-ADA output. Auditees’ experience of dissonance in the auditor’s knowledge and expertise is also rooted in what auditees suggest is an inability to properly integrate H-ADA findings with audit evidence. The method used by the H-ADA identifies the highest-risk claims to audit through targeted sampling that is common to risk-based audit sampling (DHHS 2014, 2015).

References relate to a participant number in Table 1. We edited quotes for brevity and clarity, mainly to adjust for stuttering, to edit slang words, such as “sorta,” “like,” and “yeah,” and to remove filler words marking hesitation in speech such as “um, you know” and “kind of.”

The ZPIC firms’ internal policies and procedures acknowledge the potential for audit teams to contain insufficient expertise, for example: “As appropriate, the [healthcare auditors] will seek involvement of various [CMS] subject matter experts for guidance/direction related to the contract.”

To better understand auditors’ backgrounds and credentials, we examined a sample of 180 auditor profiles from public data on LinkedIn. Using LinkedIn company profiles, we estimate that the four ZPIC firms employ approximately 3,000 people, not all of whom work on healthcare audits. As we are interested in healthcare audits, we searched LinkedIn people profiles using key words, such as “Zone Program Integrity Contractor,” “ZPIC,” and the names of the ZPIC firms. We reviewed profiles associated with these hits until we reached about 5 percent of our estimate of ZPIC firm employees. The auditors in the sample come from a variety of backgrounds, including law enforcement, healthcare practitioners, and medical claims analysts. However, only 16 percent of the profiles examined reflect a healthcare background, whereas 24 percent have law enforcement backgrounds. Of the profiles examined, the most prevalent certification was the Certified Fraud Examiner (CFE), yet less than 14 percent of the individuals in the sample present themselves as holding a CFE certificate. Another 4 percent indicate being certified as an Accredited Healthcare Investigator (AHFI). We identified one CPA.
This method deviates from random sampling since the highest-risk claims are not representative of the entire population of claims. Auditees highlight the auditors’ lack of understanding of sampling concepts and processes when discussing the auditors’ techniques for extrapolating errors to the population. For example, auditees report that auditors examined the H-ADA to identify a sample of high-risk claims and then extrapolated the audit error findings across the entire population of claims as if the targeted sample were representative of the population.

We were looking at “how did they come up with this” because they had extrapolated 150, 180 charts. They had extrapolated whatever they thought was wrong with those charts, whatever missing items, or whatever they felt was wrong with that, they extrapolated that number to I don’t know what number of the universe… [They extrapolated] over the whole billing, over the whole, I don’t know how far back they go, to my inception, to the beginning of when I started billing, I don’t know. (Exec10)

In response, some auditees hire their own “experts” to examine the validity of the auditor’s method of extrapolating errors, noting:

[W]e were able to get the paperwork that they [auditors] used to formulate this [extrapolation]… she [our statistician] literally tore these people up. As to how inept, how ridiculous their formula was, and they couldn’t document it, they couldn’t back into how they got to this number…She wrote a paper on that and…we took that to the judge and the judge overturned it. (Exec10)

[Our consultant] wrote an appeal to the extrapolation and they threw the extrapolation out [in an early stage of the appeal process] because of…data deficiencies, whatever, the way they calculated they couldn’t reproduce…we had paid two statisticians to review the extrapolation and we submitted one of the statistician’s reviews. (Exec13)

[The Ph.D. that put that [report assessing the extrapolation] together said…the ZPIC process did not follow this step, did not follow that, as required by the contract with Medicare, they didn’t validate this…in short, their extrapolations are not reliable. (Exec14)

This is consistent with auditees’ perceptions of deficiencies in the auditors’ knowledge of sampling and extrapolation of errors, as the auditors do not seem to understand the assumptions underlying their audit approach (Andon et al. 2015, 88). Deficient techniques for extrapolating audit errors can significantly impact audit outcomes. In conveying their healthcare audit experience, auditees highlight the auditors’ failure rate in reporting erroneous findings considering that the appeals process substantially reduced the initial fines for overpayments levied on their organizations.22

They [auditors] gave me a typical 70–80 percent denial rate and then extrapolated $750,000, and out of 40 claims almost all of them were bad according to them, and the ALJ [administrative law judge] they overturned almost all of them…in the end it was $90,000. (Exec07)

On a $72,000 Medicare audit over a three-year period of time the ALJ found that, that the government really was only due $1,500 some odd dollars, that’s a less than 3 percent error rate [from the initial fine]. (Oper08)

Of the purported erroneous claims identified by the auditors, approximately 20 percent of those are ultimately collected by CMS (OIG 2017). This suggests that 80 percent of alleged improper claims that the auditors report to Congress are invalid. The auditors may report large findings to Congress to demonstrate their knowledge and expertise. However, expertise is associated with performance (Knapp and Knapp 2001), and such a high failure rate suggests poor performance, casting doubt on the auditors’ domain-level expertise. Thus, whereas professionals are expected to hold a unique set of knowledge and expertise (Kultgen 1988; Covaleski et al. 2003; Susskind and Susskind 2015) and to appropriately signal that knowledge and expertise (Kimball 1995; Kultgen 1988; Susskind and Susskind 2015), this section demonstrates how auditees delegitimize the contracted auditors by expressing skepticism as to whether these auditors hold the appropriate knowledge and expertise in relation to using H-ADA to interpret audit evidence. Rather, auditees appear to see the auditors as novices who are unable to interpret system outputs and apply appropriate judgment in decisions (Arnold and Sutton 1998; Sutton et al. 2023).

**Application of Judgment to Data Analytic-Driven Audits**

In addition to knowledge, expertise, and credentials, auditees convey experiences regarding how the auditors apply judgment in data analytic-driven healthcare audits. The literature characterizes professionals as applying a unique set of knowledge and expertise to subjective decision-making (Kultgen 1988; Covaleski et al. 2003; Susskind and Susskind 2015). The

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22 Healthcare providers may appeal fines levied on them in a sequential process that involves (1) redetermination, (2) reconsideration, (3) an administrative law judge (ALJ), (4) a Medicare Appeals Council, and (5) U.S. District Court.
abstract nature of knowledge and expertise indicates that professionals make judgments that cannot be preprogrammed or reduced to a set of rules, allowing discretion in coping with unforeseen problems (Larson 1977; Abbott 1988; Susskind and Susskind 2015). In contrast, auditees suggest a lack of professional judgment and discretion in how the healthcare auditors process findings.

This lack of professional judgment stems partially from auditees’ perception as documented previously that the auditors have no legitimate basis for an opinion about healthcare systems and claims, for instance, who can prescribe treatment and what treatment to prescribe. Medical records may be subject to scrutiny related to the necessity of care delivered, but such scrutiny requires substantial professional judgment and not simply a checklist mentality. However, according to auditees, the auditors’ judgment of documentation of medical treatments and care is overridden by AI-enabled tools and analytic outputs that are focused on a set of preprogrammed risk factors and criteria beyond the auditees’ control, as in the following:

These claims, it’s just a computer doing what a computer is supposed to do, but the computer is no better than the operator who put the data in, and the data, they could have asked us, we could’ve explained that within an hour, within a couple of days if they’d asked us what that was. (Exec06)

They randomly select what their drivers are nobody really knows, they randomly select different facilities, different bills, and say “we need more information,” and...if you can’t provide appropriate documentation, they’re going to expand their sample...So, your best behavior is...to make sure all the’s are dotted and the t’s are crossed. [Not doing] that provides the government with an ability not to pay for services rendered. (Exec04)

Consequently, auditees dismiss the healthcare auditors’ ability to exercise professional judgment, indicating that the auditors’ findings focus primarily on issues surrounding supporting documentation for analytic outputs that reduces the auditors’ judgment to a series of rules (Larson 1977; Abbott 1988). As another example, auditors identify claims as being erroneous when auditee documentation contradicts the auditor’s rules, despite the documentation being completed in accordance with established healthcare regulation and procedures, as in:

[W]e use electronic signatures with a lot of the doctors… and Medicare accepts it…when they do it electronically, the little symbol for the electronic signature also prints the date in…and they [healthcare auditors] denied those claims saying that the doctor did not sign and date the order, he just signed it and the machine dated it. (Oper04)

The auditors] pay no attention to the recent [procedural] ruling[s]...[the auditors are] not really paying attention to any of those findings...but we’re aware of them because when it happens, we receive training, and we train our staff on providing those services correctly and incorporating those particular findings so we’re not in violation and we’re not violating anyone’s rights. (Exec06)

Previous data analytic-driven initiatives have used statistics as a means of identifying risk areas for examination by auditors; however, auditees reported that the auditors deny claims based exclusively on statistics, without evaluation of their reasonableness. One auditee stated that this is the first time that providers were financially penalized by CMS using statistical analysis (Exec04). Further insights regarding the auditors’ deference to the H-ADA include that:

To be presumed guilty by a statistical analytic, has never been done before...they said [for] anybody [provider] in our sample...because they were statistical outliers, we’re assuming you did something wrong and therefore we’re not paying you...every bill that was pulled was denied 100 cents on the dollar, denied, because statistically it didn’t make sense to somebody...Statistically you can have an outlier, but that doesn’t mean you did anything wrong. (Exec04)

Finally, auditees’ healthcare audit experience suggests that reliance on the H-ADA hinders auditors’ professional judgment. Consistent with the idea that AI-enabled tools control and facilitate audits and support auditors (Banker, Chang, and Kao 2002), the H-ADA is intended to facilitate the healthcare audit, where “[the auditors] use the [H-ADA] to more efficiently and effectively fulfill their responsibility to investigate Medicare fraud in their designated region...and to rapidly implement a potential administrative action” (DHHS 2012, 15).

Accordingly, the H-ADA centralizes and standardizes judgment and facilitates auditors targeting the highest-risk claims (DHHS 2012, 2014, 2015). This appears contrary to professional norms as the H-ADA represents a tool that restricts auditors’ ability to exercise judgment and conduct appropriate audit procedures (Dowling and Leech 2014; Boland et al. 2019). Furthermore, the H-ADA may identify a large number of exceptions, presenting the auditors with too many issues that overwhelm them and hinder decision-making (Iselin 1988). Indeed, auditees express frustration with the number of false positives identified and, in their view, treated incorrectly by the auditors. Merely identifying these exceptions is insufficient; rather, they need to prioritize exceptions, evaluate false positives, and isolate true
exceptions. Where the system does not identify these “exceptional exceptions” and guide auditors to focus on the most suspicious items (Issa and Kogan 2014), auditors must use professional judgment to do so.

Yet our analysis suggests that auditees believe the auditors blindly follow the prescriptions of the automated tool without truly understanding how to aggregate and assess the audit evidence. This apparent technology dominance of novice auditors is contrary to traditional perspectives of audit professionals placing a strong emphasis on maintaining their decision-making autonomy (Covaleski, Dirsmit, Heian, and Samuel 1998; Arnold and Sutton 1998). Rather, in our setting, the auditors exhibit an automation bias where a warning system (i.e., the H-ADA red flag) triggers the reactionary need to do something rather than assess whether something needs to be done (Skitka et al. 1999; Sutton et al. 2023). This reaction to red flags is consistent with prior research showing that novices increase bias in decision-making when using artificial intelligence-based tools, whilst experts understand context and reduce bias (Arnold, Collier, Leech, and Sutton 2004).

Data Analytic-Driven Audits and the Public Interest

Finally, auditees’ experiences undergoing data analytic-driven healthcare audits suggest a concern over the public interest implications of the contracted auditors’ technology dependence. Professionals are suggested to emerge and maintain their existence by a need for activities that protect the public interest and positively address societal issues (Abbott 1988; Kultgen 1988; Susskind and Susskind 2015). Audit professionals claim a public interest orientation in the conduct of their work that has often been questioned in the accounting literature in terms of what it means for audits to serve the public interest (Parker 1994). As we have not found specific instances of the auditors making such claims, the extent to which the auditors consider the public interest in the performance of their audits is unclear. However, CMS emphasizes the government’s commitment to ensuring that neither provider operations nor quality of care are adversely impacted by data analytic-driven healthcare audits (DHHS 2012). At the same time, the U.S. government’s annual reporting around healthcare audits focuses on their “success” in cracking down on waste and fraud.

In undergoing healthcare audits, auditees acknowledge the positive public interest implications of the government’s initiative to use data analytic-driven healthcare audits to identify providers committing healthcare fraud and even shut them down.

If they [auditors] are there and you [a healthcare provider] did commit fraud, I’m happy as heck. (Exec07)

The ones [healthcare providers] that are blatantly across the board committing fraud, shut them down, I have no problem with that. (Oper11)

[Convicted fraudsters] need to be handled appropriately and should be shut down. (Exec17)

Less extreme, but still critical, are auditees’ expressions of how their experience of undergoing data analytic-driven healthcare audits may lead them to deter healthcare audits of this nature and potential punishment by simply decreasing the number of patients treated or to (in)voluntarily cease treating patients in government-sponsored healthcare programs altogether, as in:

We’re going to stop taking Medicare totally, because at least we know Medicaid is going to pay. We got to meet our payroll. (Exec04)

I had to stop taking Medicare today. I cannot afford to pay staff, phone, lights with no financial relief. (Exec06)

We are making an assessment if we want to just stay away from Medicare patients all together…this [audit] process bankrupts companies. (Oper06)

The healthcare governing agency acknowledges that providers have “voluntarily withdrawn from Medicare after the start of a targeted investigation by our program integrity contractors” (DHHS 2015, 15). As healthcare providers stop accepting Medicare, choices for Medicare patients become more limited. This has severe public interest implications for areas with already limited healthcare providers and medical facilities (Eldenburg and Krishnan 2003). Furthermore, the jurisdiction of the auditors has since expanded to other government-sponsored healthcare programs (Centers for Medicare and Medicaid Services (CMS) 2018b), which may affect healthcare providers’ ability to sustain operations by diversifying their services and limit the country’s most vulnerable patients’ choice of providers.

Indeed, auditees also noted the potentially significant impacts that H-ADA can have on a healthcare provider’s ability to provide service and sustain operations. For example, one auditee described that they were identified for a healthcare audit because they had lower costs than similar providers in the region. This auditee expressed frustration with being targeted by the H-ADA for having lower expenses than other providers and the auditors following up with audit procedures to examine “the problem,” which the auditee argued was saving the government money (Exec07). Another
auditee described how despite being by far the largest provider in their subindustry, the H-ADA triggered their healthcare audit due to the amount of supplies procured for administering a common healthcare procedure, procurement that was then prohibited as part of the healthcare audit process solely due to the extent of supplies procured being flagged by the system and then deemed an irregularity by the auditor (Oper04). The behavior is consistent with a type of automation bias known as “errors of commission,” where users of AI-enabled tools feel the need to act when receiving an alert from the system (Skitka et al. 1999; Sutton et al. 2023).

Other auditees express how auditors’ technology dominance during the healthcare audits, namely, the lack of judgment applied to analytic outputs that may represent false positives, can ultimately impact a provider’s ability to sustain operations:

[S]mall mom and pop [healthcare providers] that are just a one location thing, if they ever faced this, they would be out of business [due to lack of resources to challenge the allegations]. (Exec09)

[W]e’ve heard that there are companies [healthcare providers] that completely shut down. And then when they go to appeal [the outcome of the data analytic-driven audit] the judge rules in their favor, but there is no company anymore. (Oper06)

I bought one of my nursing homes because they had gotten hit [with allegations of fraudulent claims] and couldn’t survive this [the appeals process]. (Exec01)

Thus, for a provider to close down specifically due to a healthcare audit represents a salient fear, as many auditees have declared bankruptcy due to restrictions imposed by the healthcare audit, limiting the number of healthcare providers available to deliver Medicare services.

In addition to disruptions in the provision of service and to provider operations, auditees perceived hindered quality of care because of their healthcare audit. In line with Pflueger’s (2016) suggestion that accountants largely overlook the quality of care delivered by healthcare providers, a lack of focus of the auditors on the relationship between data analytic-driven audit findings and quality of care is troubling to auditees who prioritize patient experience/satisfaction. Auditees convey their perceptions of the way the data analytic-driven healthcare audit may impact sufficiency or quality of care as follows:

[The auditors are] not really looking at what we did for the patient, what’s wrong with the patient, how we took care of the patient, how we had a good quality report. (Oper10)

[T]he most challenging process was the allocation of resources and time spent from our team that took us away from patient care. Because most of our really, really good clinical nurse leaders needed to be putting charts together [for the auditor]. (Exec02)

For auditees, the auditors’ demands for documentation supporting the claims flagged by the AI-enabled tool as well as the demands the auditees meet in formulating their appeals redirected excessive amounts of time and resources away from quality of care, especially since the vast majority of those claims are eventually overturned. Considering the themes in this section, a picture comes together from auditees that suggests that AI-enabled tools and analytics create new considerations around reliance on the tool’s analytic output and how this technology dominance manifests itself in blinding auditors to public interest implications.

V. DISCUSSION

In the context of public sector healthcare audits, an AI-enabled tool that uses analytics in the form of algorithms and data models detects healthcare service payment outliers and identifies the auditees, e.g., healthcare providers, in which the outliers occurred. With these analytic-driven outputs, contracted auditors conduct audits of the payment outliers classified as high risk along with any other payments subsequently deemed high risk as the audit proceeds. Consistent with the theory of technology dominance, we observe paraprofessional auditors23 being dominated by the technology, unable to bring the appropriate expertise to an engagement to question the AI-enabled tool’s risk identified outputs. Perhaps even more importantly, we observe the role of technology dominance effects on deprofessionalization.

The use of AI-enabled tools and analytics in audits is generally anticipated to reduce the time professional auditors spend on lower-level, labor-intensive tasks and reallocate this time to judgment-intensive tasks (Brown-Liburd et al. 2015; Susskind and Susskind 2015; Cooper, Holderness, Sorensen, and Wood 2019). What we see in the context of healthcare audits, however, is that AI-enabled tools do not necessarily reduce the time spent on labor-intensive tasks if novice auditors employing the data analytic do not understand the process by which the analytic output was determined.

23 We define the auditors as paraprofessionals based on the way they are defined in the audit literature and the correspondence with the way that the auditees consistently described the auditors they encountered, as well as the judgments and outputs generated by the audit teams. Paraprofessional is not a term the participants used.
or the context in which the output should be interpreted (Arnold and Sutton 1998; Sutton et al. 2023). Instead, healthcare auditors dedicate time and resources to auditing, and auditees expend time and resources to fulfill documentation requests while defending claims initially identified as high risk by the tool that are in fact valid. Advanced technologies and analytics may be effective at identifying statistical anomalies and outliers, but outliers may also merely represent false positives (Vasarhelyi, Kogan, and Tuttle 2015) with legitimate explanations (Kogan, Alles, Vasarhelyi, and Wu 2014). For instance, the H-ADA may yield outliers that are clearly explainable, such as healthcare providers with disproportionately high or low expenses, due to specialty practices or those garnering efficiencies by exhibiting best practices, respectively. As such, the potential usefulness of AI-enabled tools and analytics to reallocate time toward judgment-intensive work is limited by the capabilities of the human users (Alles and Gray 2016).

In understanding and interpreting analytic outputs: knowledge, expertise, and judgment remain paramount to the extent that an auditor may not be considered credible without these capabilities (Mayer-Schonberger and Cukier 2013). Indeed, auditees questioned the auditors’ credibility as the auditors seem to indiscriminately report alleged high-risk claims associated with outliers identified by the AI-enabled tool, with the tool supplanting the auditor as the expert in not only identifying but also “interpreting” high-risk activity. In addition, auditees presented their perception of auditors’ lack of credibility relative to the auditors’ backgrounds and credentials in law enforcement, delegitimizing the healthcare auditors by portraying them as not “professionally qualified” (Andon et al. 2015, 84). To the extent auditees claim greater knowledge and expertise than their auditors (Gendron et al. 2007), auditees imply only individuals with certain backgrounds and experiences have the “right” to inhabit audit roles and perform specialized audit tasks.

When faced with performing a task that they do not have the knowledge or expertise to complete, auditors are expected to acquire the desired expertise or engage a specialist. Extending beyond the financial statements, audits may necessitate extending the scope of recruitment to specialists (in law, IT, strategy, etc.) with different (and sometimes conflicting) social and professional dispositions (Malsch and Gendron 2013). In the healthcare audit context, the government agency may have sought auditors with a heavy law enforcement background as law enforcement lends to a focus on reporting fraud, illegal acts, and criminal behavior in a way that traditional audit backgrounds might not. Alternatively, the H-ADA may have been construed by the contracting firms as a criminal detection system warranting a corollary response. Thus, it could be argued that the auditors auditing high-risk claims may not need to be professional auditors in the traditional sense, but rather paraprofessionals who carry out prescribed mechanic tasks as guided by the analytic output, which they then defer to in justifying their judgments and behavior.24

At the same time, the programming of algorithms that guide AI-enabled tools such as the H-ADA may initially take on biases and inherent limitations of human judgment, later autonomously adapting the original algorithms based on the situations encountered in ways that may not be predictable and may raise ethical considerations (Sutton et al. 2018; Munoko et al. 2020). The increased use of paraprofessionals may be all the more worrying in light of the argument that auditors need enhanced moral abilities to cope with increasingly complex and challenging environments (Ponemon 1993), including technological complexity. As such, not only human judgment, but professional judgment, remains critical, and AI-enabled tools and analytics should not be considered a substitute for expert decision-making around audit findings and outcomes (Sutton et al. 2018).

In the context of healthcare audits, the auditors essentially immobilize the auditee, lending to perceptions of auditors as exhibiting “unprofessional” behaviors and auditees’ delegitimizing discourses around the healthcare audit. This immobilization is manifest in different ways, several of which are reminiscent of what Andon et al. (2015, 85) find in new audit contexts, where an uncompromising and brusque posture is unwelcomed by auditees who lambast the auditor for “Gestapo-like” tactics (Exec01). Similar to Andon et al. (2015, 85–86), our healthcare auditors draw the ire of auditees for what the auditees “consider to be unnecessary attention to petty concerns and dispassionate treatment,” which materialize as a focus on documentation issues or technicalities and disregard for patient care, the difference being the role that AI-enabled tools and analytics play in augmenting the healthcare auditors’ self-assuredness and perceived dominance, not only around petty concerns and dispassionate treatment of the auditees, but around audit outcomes that have significant public interest implications (Koref, Weisner, and Sutton 2021). Whereas public accountants have themselves been under fire for exhibiting declines in professionalism (Dirsmith, Covaleski, and Samuel 2015), through the reduction of judgment in the commodification of audit procedures (Suddaby and Greenwood 2001) and perceived conflicts in auditors’ public interest orientation (Fogarty et al. 2006), technology dominance in the healthcare audit seems to exacerbate such concerns from the standpoint of auditees’ subjected to data analytic-driven healthcare audits.

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24 The CMS Statement of Work (CMS 2007) specifies a broad range of individuals that could be used on audit teams, that in some cases provide limited experience with certain technical medical and Medicare knowledge or criminology backgrounds, but in many other cases do not require more than a high school diploma.
VI. CONCLUSION

Accompanying the rise in technology enabled tools and new types of data to be analyzed (Brown-Liburd et al. 2015; Power 2021), this paper explores the application of AI-enabled tools and analytics within a public sector audit context. Specifically, we conduct field research to investigate how auditees experience data analytic-driven audits conducted by auditors in the public sector audit of government-sponsored healthcare programs. We show how auditees’ experiences undergoing AI-enabled, data analytic-driven audits are understood in relation to their perceptions of auditors’ knowledge, experience, and certification; application of judgment; and public interest orientations. These experiences suggest the need to further reflect on the displacement of knowledge workers with paraprofessionals and relying on AI-enabled tools and analytics as audit solutions (Sutton et al. 2018). Furthermore, our work alludes to the way that auditees position their experiences in relation to expectations for what it means to be an auditor and to conduct a “legitimate” audit. For our auditees, the healthcare auditors conduct on the audit was anathema to idealized professional norms (i.e., only “professional” auditors have the right to inhabit auditing roles) (Andon et al. 2014, 83) and therefore was delegitimized by the auditees, suggesting there is more to learn about the way AI-enabled tools and analytics may reconstruct traditional professional norms (Sutton et al. 2023; Susskind and Susskind 2015).

Our work suggests several areas for future research, particularly related to AI-enabled tools and data analytics in the broader audit context, in the public sector context, and specifically in the field of healthcare. First, our research indicates the need for future research on the role and power of AI-enabled tools and analytics in different audit contexts (Appelbaum et al. 2017; Williams 2013). Within the healthcare audit context, our findings are potentially exacerbated by limitations of paraprofessionals hired by the contracted audit firms and by apparent poor supervision and review of work conducted by the paraprofessionals. The outcomes may be altered by using better trained and more experienced audit staff and through better supervision from high-expertise senior auditors. Still, technological tools enable the commodification of audit procedures and provide auditors with “expert” justification to structure and support audit work (Banker et al. 2002). Reliance on the technological tool allows auditors to reduce human judgment and defer to the tool as the decision maker (Dowling and Leech 2014; Boland et al. 2019), and their design has been found to often constrain the ability of supervisors to focus on key supervision activities in the face of structured documentation constraints (Dowling and Leech 2014). In the long-term, the structure behind these systems can hinder development of individual expertise and a field’s advancement of knowledge (Arnold and Sutton 1998; Sutton et al. 2023). Whereas public accounting firms may hire paraprofessionals guided by analytics in an effort to constrain costs, the results of this study show auditees delegitimize this approach in line with scrutiny facing the public accounting profession for depersonalizing trends (Dirsmith et al. 2015). Such use of analytics has already been indicated to have potentially adverse societal implications, not to mention dehumanizing aspects (Arnold and Sutton 1998), that may be exacerbated in the public sector field of healthcare.

Relatedly, future research should expand our understanding of the societal consequences of audits and auditors’ activities in different contexts, particularly in the public sector. Government reports discussing the auditors’ actions focus on financial metrics and do not discuss issues of public health and the delivery of healthcare services to the country’s aging population during and after healthcare audits (e.g. patient care suffering and providers refusing patients) (DHHS 2012, 2014, 2015)—concerns raised consistently by participants in this study. These effects may be particularly present in this study’s context, where the auditors are rewarded for additional documentary evidence gathering and extension of investigations under their costs plus contract structure (obtained via FOIA requests) coupled with the need to justify the benefit of their services on an ongoing basis (DHHS 2012, 2014, 2015). Such concerns not only challenge suggested public interest gains emerging from the healthcare audits but also align with prior research noting how accounting may “crowd out” other values by focusing on action that “economizes” and “financializes” organizational performance (Millo, Power, Robson, and Vollmer 2021). This crowding out may be particularly concerning in public sector audits as they represent contexts where audit failures have implications for societal wellbeing (Mashaw and Marmor 1994) that extend far beyond monetary and reputational damage to investors, clients, and public accounting firms (Chaney and Philipic 2002; Newman, Patterson, and Smith 2005) and at the extreme, in the healthcare context, to potential loss of life (Sherer 2004). This implies the imperative for public sector audit mandates relying on AI-enabled tools and analytics to consider an appropriate (and perhaps broader) range of metrics to evaluate audit objectives, processes, and outcomes that may not be easily captured and interpreted by AI-enabled tools alone.

Lastly, the development of the H-ADA demonstrates how technologies can be used in conjunction with political rationalities (Free, Radcliffe, Spence, and Stein 2020). For instance, mandates to employ AI-enabled tools and analytics may represent political activities used to push particular agendas that create mirages of substantive financial savings without adequate consideration of public interest implications. Our case alludes to the H-ADA being used to politically remake and define a healthcare patient in data analytic terms in an attempt to reduce waste (Preston 1992; Llewellyn 1998;
Kurumäki 1999), blurring the line between cost and caring (Llewellyn 1998; Pflueger 2016). Where substantial public resistance may be directed at efforts toward decreasing the availability or quality of government-sponsored healthcare, contracting with auditors to detect and prevent fraud results in less public scrutiny and provides an example of using accounting information and technology to legitimize decisions from a cost perspective (Nielsen, Mathiassen, and Newell 2014). At the same time, in demonstrating the potential harm the technology produces to the quality of healthcare, our case provides an example of the unintended consequences of AI-enabled tools and analytics (Radcliffe, Spence, and Stein 2017). Future research may examine the purpose, objectives, and outcomes of data analytic-driven audit mandates in terms of their political aims as well as the role of audit and auditors in contributing to policy making or policy aims. Those aims may also be understood through further study of auditee responses, including resisting government audit mandates (Malsch and Gendron 2011), reducing the risk of audit (Power 2013), or succumbing to the objectives of the political apparatus. Overall, we have much more to learn about applications of audit technologies in a data analytic-driven world both in a public sector audit context and beyond.

As further research is developed within these areas, consideration should be given to the boundaries of current research and how further understanding might be gained from beyond those boundaries. First, our focus has been on auditees experiencing detailed healthcare audits related to primarily documentation errors. Other studies might focus on stakeholders such as auditors and how they perceive the construction of AI-enabled audits and the judicial appeal system that sees both cases of irregularities and significant cases of actual fraud. Although it is common in audit research to focus on one group of stakeholders, future studies may want to consider multi-dimensional participant pools that draw perspectives from auditees, auditors, the judicial system, regulators, and/or other stakeholders. Second, despite a “family resemblance,” forensic auditing is a more focused engagement that may have a greater presumption of wrongdoing, and other audit contexts might create a less adversarial positioning by the auditor. Third, the market dynamics of the healthcare audit context where a political/governmental body determines the need for audit and to whom the auditor has primary responsibility may be quite different from audit contexts where the auditee has a greater influence on the audit and auditor decision, or where the independent body overseeing the audit contractor has a more service quality focus as opposed to a focus on potential waste of resources and associated cost savings. The current study only begins to unveil the impacts of AI-enabled technologies on auditors, the audit process, and the auditee-auditor relationship.

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