DOI: 10.1111/jifm.12148

ORIGINAL ARTICLE

JOURNAL OF INTERNATIONAL FINANCIAL MANAGEMENT & ACCOUNTING WILEY

The effects of person-specific, task, and environmental factors on digital transformation and innovation in auditing: A review of the literature

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Abstract

This study reviews literature examining digital transformation in the external audit setting. Our review will inform the standard-setting initiatives of the International Auditing and Assurance Standards Board (IAASB) related to the use of technology in auditing. We identified 36 articles on digital transformation in the external audit published between 2000 and 2021 across 20 journals ranked A*, A, B, and C on the Australian Business Deans Council (ABDC) 2021 Journal Quality List. We also identified 18 advanced working papers. These articles cover conceptual frameworks and archival, experimental, interviews, case studies, and survey research methods. Fifty percent of the published articles appear in A* or A journals, of which nine were published in one of the premier six accounting research journals (i.e., A*) since 2020. This trend is a promising sign that there appears to be increasing interest in publishing digital transformation-related research in these general interest journals. We use the Bonner judgment and decision-making framework, coupled with the four primary data analytic tools, to organize and evaluate the literature. This study examines descriptive and diagnostic analytics; more complex techniques, such as predictive and prescriptive, are not as prevalent. Further, existing research insufficiently addresses how data analytic tools impact auditor judgment and decision-making, providing multiple future inquiry lines.

KEYWORDS
audit innovation, auditor JDM, digital transformation, literature review

1 | INTRODUCTION

In the 20th and 21st centuries, the accounting profession has witnessed a transformation in auditing with the advent of computers, which enabled computer-assisted auditing techniques. Like any change, auditors were reluctant to adopt that technology, though it could improve audit efficiency and effectiveness (e.g., Bierstaker et al., 2014). Trends in technology present a moment that could be transformational. That is, the types of emerging technologies being developed or adapted to the audit setting will be revolutionary. Much of the prior academic and practitioner research focuses on artificial intelligence (AI) and advanced analytics (e.g., leverage data and technology to enhance audit quality). However, auditors, accounting firms and their audit clients are at different points along the digital transformation journey (e.g., Austin et al., 2021; Grant Thornton, 2020). The four general types of advanced analytics are: descriptive, diagnostic, predictive, and prescriptive. These advanced analytics offer significant value. Some firms attempt to implement the most advanced (e.g., prescriptive analytics) with little consideration to the necessary foundation provided by less complex tools (e.g., descriptive analytics). As a result, the likelihood of successful implementation decreases (e.g., Kalsbeek, 2020).

As data becomes more accessible and the volume of available data continually increases, organizations must adopt emerging technologies that enhance their ability to compete in this data-driven environment. For example, descriptive-analytic tools like visualizations permit auditors to improve audit efficiency and effectiveness by adjusting the nature and extent of audit procedures used to collect sufficient and appropriate audit evidence. However, research on external auditors' use of emerging technologies is in its nascent stage. In addition, limited research examines the behavioral and cognitive implications of auditor use of advanced analytic tools and techniques and the resulting impact on auditor judgment and decision making (JDM).

Regulators' perceptions of auditors and their firms influence the use of advanced analytics (e.g., Eilifsen et al., 2020). A perceived lack of sufficient audit standards capable of assuaging these concerns heighten auditors' hesitancy to adopt advanced analytics and other digital transformation (Barr-Pulliam, Brown-Liburd, et al., 2021). Even though clients expect their auditors to adopt new technologies, accounting firms tend to be reactive rather than proactive in leveraging technological innovations compared to their clients (e.g., Austin et al., 2021).

While current auditing standards do not preclude the use of such technology, accounting firms are concerned that the standards' explicit lack of focus on using technology could result in regulatory scrutiny. Firms also hesitate to use data analytic techniques broadly because such use will increase their legal liability if an audit failure occurs (Barr-Pulliam, Brown-Liburd, et al., 2021). Consequently, the question arises on whether audit evidence standards focused explicitly on a technology-enhanced audit are needed or whether the existing standards be modified to address the unique aspects of digital transformation. Irrespective of regulatory concerns, management expects that if auditors leverage technology to improve audit quality, their companies should see a decrease in audit fees based on the efficiency gains afforded from advanced analytics (Austin et al., 2021). These conflicting incentives across stakeholders create a unique and rapidly evolving challenge for external auditors.

Another important consideration is the potential disparity in emerging technologies and the phase of digital transformation across accounting firms. Specifically, larger firms have innovation leaders or organizations that help identify, develop, and otherwise facilitate the digital transformation journey. Smaller firms may be more likely to use off-the-shelf tools, placing them at a disadvantage in competing for clients and human capital (Carson & Barr-Pulliam, 2021). Further, as compliance with auditing standards is often costly, smaller firms may be unable to comply with these standards if they are too onerous, and they may be less likely to use advanced analytic tools. These concerns lead to the questions: Will this disparity potentially lead to two tiers of audit quality and the need for two sets of audit standards? To answer these questions, we need to better understand the underlying factors related to the auditors' and accounting firms' digital transformation process, differences in the use of advanced analytics between auditors and their clients and how these factors could impact audit quality.

We synthesize the prior and emerging academic research and develop future lines of inquiry related to the impact of digital transformation on external auditors' JDM.[1] Based on prior literature, our present understanding of emerging technology and digital transformation stem mainly from the internal audit perspective (e.g., Christ et al., 2020). The regulatory environment, organizational structures and ability to access data enabling these technologies give internal auditors the advantage (e.g., Barr-Pulliam, Joe, et al., 2021). Given the lack of research targeted explicitly toward external auditors, we begin by reviewing current and proposed practice areas of interest to audit standard-setting bodies, with implications for other bodies arising from these considerations. We rely on the person, task environment (PTE) framework described by Bonner (2008) to evaluate the current literature. We also discuss academic studies that provide, more broadly, insight into the potential impact of more advanced technologies used in various phases of the audit process (e.g., risk assessment, substantive procedures).

Our review includes 54 academic articles—36 research articles and 18 articles that describe emerging technology or offer opportunities for future assurance services—published between 2000 and 2021 in more than 20 journals included on the ABDC Journal Quality list.[2] Given the nascent research on external auditors' use of advanced analytics in top-tier journals, we also include publicly available working papers on SSRN. We complement and extend previous behavioral research by Austin et al. (2021) and Cao et al. (2021) and previous reviews of digital transformation research in the internal audit setting (e.g., Christ et al., 2020; Tang et al., 2017).

To our knowledge, we are among the first to conduct an extensive review of the growing academic literature on digital transformation in the external audit arena. Prior research offers conceptual frameworks (e.g., Appelbaum et al., 2021; Dai & Vasarhelyi, 2017) and thought pieces related to education (e.g., Vincent, Igou, et al., 2020; Vincent, Skjellum, et al., 2020). Notably, relatively few studies we identified were published in top tier (e.g., Financial Times 50 journals) or general interest journals. As the proliferation of technology and auditors' comfort with such technology increases, we expect this trend to change course. We provide suggestions for future research motivated by the IAASB's and other stakeholders' focus on digital transformation in auditing. Informed by the JDM framework, our review offers fruitful pathways for academics to focus more on conceptual frameworks and technical descriptive studies while shifting the focus to behavioral implications. This focus could increase the likelihood of publication in general interest, top-tier business journals.

The remainder of this paper is structured in eight sections. Section 2 discusses the relevant auditing/assurance standards. Section 3 describes the types of advanced data analytics currently used by, or proposed for use in, external audit, and Section 4 discusses the JDM framework. Section 5 describes our methodology, and Section 6 reviews the literature in terms of two broad categories—the relevant environmental, person-, and task-specific factor influencing JDM; and the advanced analytic type. Section 7 provides a discussion of emerging technology that presents new audit/assurance lines for auditors. Section 8 provides ideas for future research, and Section 9 concludes.

2 | BACKGROUND TO ASSURANCE STANDARDS

In 2016, the IAASB issued a Consultation Paper titled *Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics*. The IAASB, through its Data Analytics Working Group (DAWG), provided insights into the opportunities and challenges related to the use of technology, specifically data analytics, in the external audit. The call for comments yielded 51 responses from various stakeholders. A primary focus was to gain stakeholder input regarding whether new or revised international standards or guidance may be necessary regarding the use of data analytics. The Consultation Paper acknowledges concerns raised by auditors that current International Standards of Auditing (ISAs) (and similarly auditing standards promulgated by the Public Company Accounting Oversight Board [PCAOB] in the United States [US]) do not prohibit use of data analytics in audit engagements.

Comments on the Consultation Paper focused mainly on how data analytics could impact the perceived persuasiveness of audit evidence. A comment letter from the Rutgers' Continuous Audit and Reporting Laboratory (CarLab) noted that regulators should consider whether the use of audit data analytics automatically addresses the sufficiency and appropriateness of audit evidence. For example, auditing standards define sufficiency as the measure of the quantity of audit evidence needed based on the auditor's assessment of the risks of material misstatement (the higher the assessed risks, the more audit evidence is likely to be required). However, Brown-Liburd and Vasarhelyi (2015) note that, because audit data analytics can be utilized to analyze and test complete populations of complex transactions and balances, the sufficiency of audit evidence may not be the primary issue. Instead, the shift in focus will most likely relate to the timely accessibility of the relevant data and the various data analytic tools auditors use to analyze and interpret the data in a more meaningful and effective way. Appropriateness is the measure of the quality of audit evidence; that is, its relevance and reliability in providing support for the conclusions on which the auditor's opinion is based. Thus, the traditional approaches for evaluating relevance and reliability may not apply. While relevance will likely continue to be determined by judgment, such judgment will be subject to evaluation by formalization, as many audit tests will be formalized into computer procedures that do not currently exist. In contrast, reliability will likely increase because, in general, automated data extraction and utilization by formal models are much more reliable than manual processes (Brown-Liburd & Vasarhelyi, 2015). Therefore, standards setters and regulators should be proactive in addressing the impact of emerging technology on traditional forms of audit evidence because the conventional view of evidence may no longer be sufficient (Eilifsen et al., 2020).

Responsing to key messages from stakeholder comments on the 2016 Consultation Paper, the IAASB Technology Working Group (TWG) in 2020 issued nonauthoritative support materials intended to provide auditors with guidance in understanding the relevant consideration for the use of automated tools and techniques (ATT) on audit engagements. The TWG also explores the use of emerging technologies in accounting and how the IAASB can respond to these technological developments with new or revised standards. Additionally, the IAASB has commissioned the Audit Evidence Working Group that examines audit-evidence-related issues resulting from technology use and aspects of professional skepticism. Both workgroups' goals are to develop nonauthoritative guidance. These nonauthoritative materials focused on the use of ATT related to audit documentation, identifying, and assessing the risk of material misstatement, performing audit procedures, and addressing the risk of overreliance on technology and information generated by a client's information systems.[3] Further, advancements in and the use of technology are significant IAASB's strategic objectives influencing standards and future activities. Specifically, the 2020–2023 Work Plan focuses on emerging technologies including AI, robotics, blockchain, cloud computing, social networks, and digital payment platforms, and how these technologies are used in audit and assurance engagements and the way they influence structure and interation of engagement teams (IFAC, 2020).

3 | TYPES OF ADVANCED ANALYTICS

Several tools are available for auditors in audit engagements ranging in complexity and value to audit quality and auditor JDM. Larger firms have the infrastructure to develop customized tools, while smaller firms may purchase "off-the-shelf" tools they customize for use (Carson & Barr-Pulliam, 2021).

One risk that could threaten the efficacy of these tools is the tendency of audit firms and their clients attempting to "walk before they crawl," that is, the tendency to jump in with the most advanced analytics without regard to the analytics progression (Kalsbeek, 2020). There are four general types of advanced analytics: descriptive, diagnostic, predictive, and prescriptive. As indicated in Figure 1, these analytics increase in relative complexity from descriptive (least complex) to prescriptive (most complex). However, the value added increases with the level of complexity of the analytic. We describe the types of analytics following Kalsbeek (2020).

Descriptive analytics often rely on historical data (e.g., revenue, expenditures, PCAOB inspection Part I findings[4]) to explain "what happened." Because this fundamental analysis focuses on past events, it helps identify patterns and trends. Visualizations (e.g., graphs, scatter plots) are common ways to present the output of descriptive analytics.

Once "what happened" is assessed, the next logical question is "why did it happen?". Diagnostic analytics help answer this question as these tools dive deeper into anomalies or trends identified by descriptive analytics. Auditors can, thus, mine the available data to further identify and evaluate patterns in the data. Visualizations and correlation tables or analyses are common ways to present the output of descriptive analytics.

Germane to auditing is evaluating "what happened and why" and moving to "what could (or is likely to) happen next." Predictive analytics provide more than an incremental step up in complexity and the value derived from diagnostic analytics. Auditors must use forecasting and predictive modeling tools to implement effective predictive analytics. However, this is not unrealistic for auditors with along-term series of client data (e.g., due to long tenure on the engagement) and that have maintained high-quality historical data. Clients could also provide

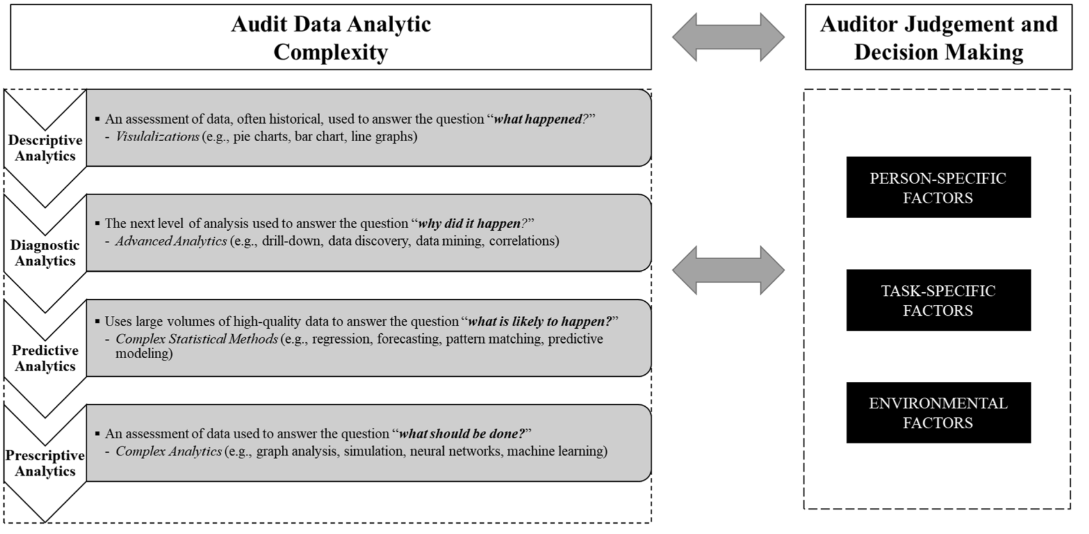

FIGURE 1 Theoretical framework. Our theoretical framework used to evaluate the 36 articles appearing in Section 6 are discussed. We discuss the framework in Sections 3 and 4

some data that enable such analyses. Auditors may be more likely to rely on data specialists to assist with the design of predictive analytics. These tools require advanced skills in statistics, experience with programming languages such as R and Python, and a sufficient understanding of the intricacies of the underlying data. For audits with less malleable audit fees, using specialists could detract from the auditor's pro-rata share of those fees (e.g., Barr-Pulliam, Joe, et al., 2021). Larger firms with this type of expertise in-house could apply those costs over their portfolio of audit clients and develop the expertise at scale.

The most complex tool is prescriptive analytics. The central question at this level regards "what should be done"? Like medical doctors, it is crucial to diagnose and reliably find support for the problem. However, determining the next steps is difficult. This analytic tool may require auditors to rely on data specialists. This tool often require complex techniques such as simulation, creating, and evaluating neural networks, applying, assessing heuristics and even machine learning. The benefit to auditors, and the insight they can provide to their clients, is the value clients expect in a data-driven business environment. For example, such analyses could be used to evaluate the risk of material misstatement given factors such as changes in point estimates, develop more granular materiality thresholds or evaluate risk exposure by accepting a particular client Figure 2.

4 | JDM FRAMEWORK (PERSON, TASK, AND ENVIRONMENT)

To organize our discussion and review of the current literature, we use the Bonner (2008) JDM framework. This framework has been used to examine auditor judgments in other settings (e.g., complex estimates) and focuses on three factors—the person, the task, and the environment (PTE). We view this framework as applicable because research in information systems suggests that personal attitudes about technology correlate with subsequent adoption of technological

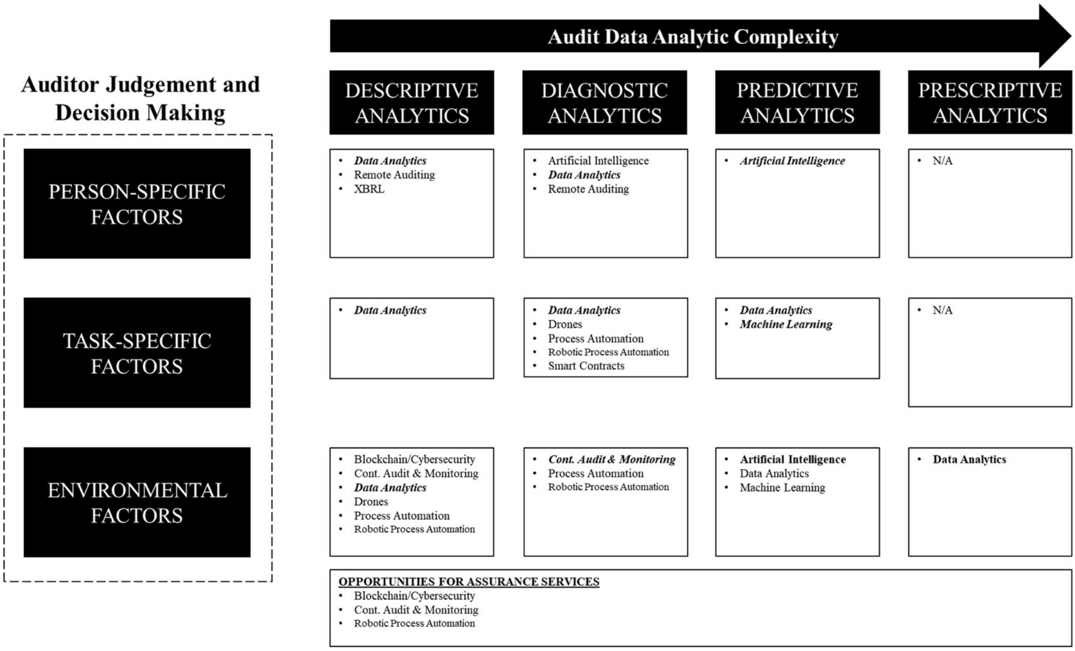

FIGURE 2 Types of technology used for digital transformation or the present opportunities for future assurance. Outlines the technologies mentioned in the 54 articles reviewed in Sections 6 and 7

innovation. For example, the extent to which an auditor developes a data analytic mindset will likely influence his/her professional skepticism and judgment when faced with increased complexity and problems associated with a technology-driven audit. Auditors are challenged to analyze transactions because the volume and complexity of accounting transactions have increased significantly due to technological innovations (Brown-Liburd et al., 2015). Additionally, Brown-Liburd et al. (2015) identified information processing weaknesses and other limitations that could hinder the effective integration of data and analytics in an audit environment. They identify information overload, information relevance, pattern recognition, and ambiguity as specific factors affecting auditors' JDM.

Big data requires large volumes of external financial and nonfinancial data. However, few instances of auditors using big data as audit evidence exist in the academic literature (Alles & Gray, 2016). Auditors may be reluctant to rely on big data because of the high false-positive rate (Barr-Pulliam, Nkansa, et al., 2021). Data analytics differs. The focus is on using technological tools to transform and examine data in new and powerful ways (Vasarhelyi et al., 2015). Auditors currently use data analytics to test populations of journal entries for red flags and anomalies based on a set of established criteria (e.g., Richins et al., 2017) in robotic process automation (e.g., Cooper et al., 2021), predictive modeling (Krahel & Titera, 2015), and to analyze unstructured data (e.g., Yoon et al., 2015).

Organizational factors are similarly important in determining how quickly a firm adopts technology. Firms increasingly look to adopt more advanced forms of AI in auditing financial statements. A challenge that firms must consider is the quality of the data used when performing data analytics and developing algorithms used in AI (Munoko et al., 2020). Audit firm quality control standards must address training data used to develop algorithms to ensure that sufficient and appropriate data avoids biased output. As Munoko et al. (2020) note, "when AI is used to provide audit judgment, objectivity can be compromised when the training data are biased" (p. 213). This intersection of organizational and personal factors appears to be missing from the literature on adoption, use and the effectiveness of data and analytics to transform the audit.

5 | METHODOLOGY

To identify accounting literature on digital transformation, we first searched the Dimensions database for articles that contain the terms "auditing" and one of the following related to technology: "emerging technology," "artificial intelligence," "blockchain," "analytics," "machine learning," "cybersecurity," "continuous auditing," "continuous monitoring," "big data," or "robotic process mining" in the field "Accounting, Auditing and Accountability." We anticipated that articles on emerging technology might be more challenging to publish in mainstream journals due to their novel nature. We included published articles and working papers in our search to overcome this "file-drawer" effect. The process yielded 8544 articles.

The summary of articles on the Dimensions database validated the importance of including working papers. The SSRN electronic journal had the highest number of articles meeting the criteria relative to mainstream journals. Since this review aims to examine the current emerging technology themes and concepts within accounting discourse, we determined that the benefits of including working papers outweigh concerns around the quality of working papers. Most articles that met the search criteria are written or published within the last decade.

We first identify the predominant themes and concepts within the literature to understand the ongoing discourse on emerging technology in the accounting field. We used the bibliometric analysis approach to identify key themes and the associated concepts for each theme. We used VOSviewer[5] software to identify predominant terms and the co-occurrence across all articles during the bibliometric analysis. The output of the process is the clustering of terms into dominant themes. The bibliometric analysis involved analyzing the abstracts of the articles to identify clusters of terms. A cluster is a nonoverlapping set of terms that have links with each other. Terms that co-occur in articles form a cluster. We weigh the strength of the links between terms based on the frequency of co-occurrences. We use Gephi[6] software to visualize the clusters identified in the bibliometric analysis.

While the initial corpus from the Dimensions database had 8544 articles, only 494 articles mentioned "technology" in their abstracts. We restricted our sample based on journal type (e.g., A*, A, B, and C on the ABDC Journal Quality list), along with working papers (e.g., SSRN Electronic Journal). This process resulted in 78 remaining articles. Of the 78 articles, 24 are relevant discussions, literature reviews and article reviews that we use to illustrate specific factors (e.g., digital transformation in internal audit) central to our review or help motivate future research (see Section 8). An additional 18 articles describe emerging technology or offer opportunities for future assurance services. We discuss these articles separately (see Section 7). The remaining 36 articles constitute our primary sample. These 36 research articles were published in 16 journals or are working papers. We classify articles using our joint PTE and analytic complexity framework (Figure 3).

As indicated in Table 1, 18 (50%) of the 36 articles were published in A* or A journals. However, we observed a relatively even mix of publications across the journal classifications, including 9 (25%) working papers. The most publications are in *Accounting Horizons* (6 [16.67%]), *Journal of Emerging Technology in Accounting* (3 [8.33%]), *The Accounting Review* (2 [5.56%]), and *Managerial Auditing Journal* (2 [5.56%]). Among the nine publications in A* journals, 2 (5.56%)

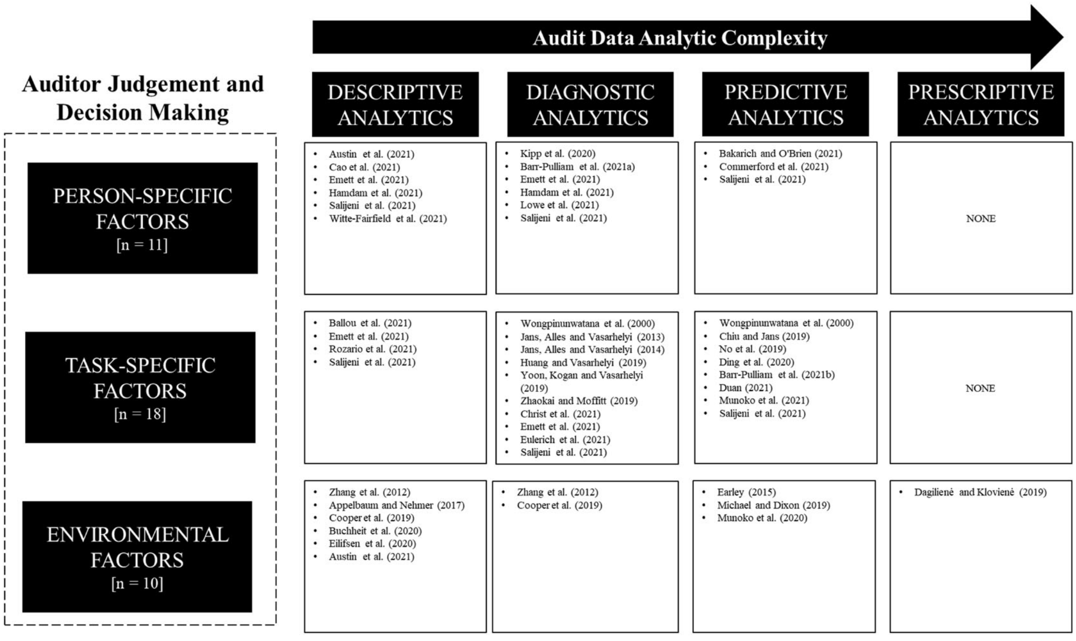

FIGURE 3 Literature organized by JDM factors and analytic complexity. We discuss 36 articles in Section 6. The total sample size (*n*) in this figure exceeds 36 because some articles apply to multiple categories. We do not include the emerging technology (18 additional articles discussed in Section 7) that describe future assurance opportunities in this figure

each are in *The Accounting Review*, *Contemporary Accounting Research and Review of Accounting Studies*. One publication (2.78%) is in the *Journal of Accounting Research, AUDITING: A Journal of Practice & Theory* and *European Accounting Review*. While one of the nine A* publications occurred in the early 2000s, the remainder were published or accepted in 2020 or 2021. This sporadic representation in A* accounting journals underscores our rationale for including more specialized and lower-ranked (e.g., C on the ABDC list) journals.

Each author reviewed and independently coded the 36 articles as (1) focusing on a person-specific, task-specific or environmental factor and (2) based on the type(s) of advanced analytic(s) it examines. We compared our coding on these two factors to determine the final categorization. For the PTE factors, we unanimously agreed on 69.44% (25 of 36 articles) of the coding and agreed on 83.33% (30 of 36 articles) of the advanced analytic coding. Where we did not unanimously agree, if at least two authors agreed on a coding category, we used that coding as the consensus. This process improved our agreement to 88.89% (32 of 36 articles) for the PTE factors and 94.44% (34 of 36 articles) for the advanced analytic coding. We resolved the remaining coding disagreements as a team and included each manuscript as described in Figure 3.

6 | REVIEW OF CURRENT LITERATURE

6.1 | Environmental factors

Over the last two decades, a radical shift has occurred in using emerging technologies such as AI within the auditing practice (e.g., Omoteso, 2012), including in emerging markets (e.g.,

TABLE 1 Sample demographics

Journal name	Rating	Sample only	Emerging tech	Overall	(%)
Accounting Horizons	A	6	0	7	8.97
Accounting Organizations and Society	A*	0	0	1	1.28
Accounting Research Journal	B	1	0	1	1.28
Accounting, Auditing & Accountability Journal	A*	0	1	1	1.28
AUDITING: A Journal of Practice & Theory	A*	1	1	2	2.56
Business Horizons	C	1	0	1	1.28
Contemporary Accounting Research	A*	2	0	2	2.56
Current Issues in Auditing	B	1	2	4	5.13
European Accounting Review	A*	1	0	1	1.28
Expert Systems with Applications	C	0	0	1	1.28
International Journal of Accounting and Information Management	B	0	0	1	1.28
International Journal of Accounting Information Systems	A	1	1	4	5.13
International Journal of Auditing	A	0	0	2	2.56
International Journal of Digital Accounting Research	C	0	1	1	1.28
International Journal of Disclosure and Governance	C	1	0	1	1.28
International Journal of Managerial Finance	B	0	0	1	1.28
Issues in Accounting Education	A	0	0	1	1.28
Journal of Accounting Research	A*	1	0	1	1.28
Journal of Business Ethics	A	1	0	1	1.28
Journal of Emerging Technologies in Accounting	C	3	3	11	14.10
Journal of Information Systems	A	1	2	7	8.97
Journal of Information Systems and Technology Management	C	0	1	1	1.28
Journal of International Accounting Auditing and Taxation	B	0	1	1	1.28
Journal of Management Analytics	Unrated	0	1	1	1.28
Managerial Auditing Journal	B	2	2	5	6.41
Review of Accounting Studies	A*	2	0	2	2.56
The Accounting Review	A*	2	0	2	2.56
SSRN Electronic Journal	N/A	9	2	14	17.95
	Total	36	18	78	100.00

Abou-El-Sood et al., 2015). Technology such as eXtensible Business Reporting Language (XBRL) was once considered the "future" of technology in financial reporting and auditing (e.g., Shan & Troshani, 2016). Regulators (e.g., US Securities and Exchange Commission), preparers, and auditors have shifted their focus to more advanced analytic tools.

A determinant of the auditor's adoption of these emerging technologies is the firm's environment. The auditor's environment includes its *clients, competitors, regulators, and* the *general regional and global technological environment* where the audit firm operates. The adoption rate, enthusiasm, and expectations of these environmental parties directly impact the audit firm's use of technologies. Eilifsen et al. (2020) find that environmental pressures play a crucial role in whether firms adopt emerging technology due to technological advancements and preferences of audit clients (particularly new ones). One group of study participants was heads of professional practice in five Norwegian offices of global accounting firms. Results of these interviews suggest that firms differ in their analytics implementation strategy. Second, based on a survey of 216 highly experienced auditors, results suggest they commonly use advanced analytics on their engagements, but not the most advanced types. The authors call for studies investigating the inhibitors and accelerants of emerging technology adoption by audit firms. Auditors also seek to stake jurisdictional claims over "new areas" by leveraging experts (e.g., data specialists) within the firm to enhance the perception that they can legitimately use and evaluate emerging technology (e.g., Robson et al., 2007). This section explores the influence environmental factors have on the adoption of emerging technologies. Because the environmental factors are not specific to any type of analytic (e.g., descriptive, diagnostic, etc.) our discussion is organized around the type of influence environmental parties exert on the auditor's adoption of emerging technologies.

6.1.1 | A regional and global shift towards digitization, automation, and business intelligence

Regional factors play a significant role in the adoption of technology by audit firms. Factors such as government influence, competition of audit firms within the region, regional regulations, and advancement of technology significantly influence an audit firm's adoption of emerging technologies (e.g., Dagilienė & Klovienė, 2019). Additionally, the region's availability of the necessary talent to develop, deploy and use these emerging technologies plays a significant role (Krieger et al., 2021). On a global scale, the development of technologies resulting in worldwide and real-time exchange of data across businesses has driven auditors to embrace emerging technologies (Appelbaum et al., 2021). Examples of such emerging technologies include XBRL, which has provided a standardized global format for exchanging business information, and blockchain that has provided global data sharing and verification opportunities.

6.1.2 | Influence of audit client on auditor's adoption of emerging technologies

The client's expectation of the auditor to use emerging technologies positively affects the auditor's actual use of these technologies (Hampton & Stratopoulos, 2016). Krieger et al. (2021) examine how audit firms adopt data analytics through semistructured interviews with German auditors and experts, finding that the environment plays a crucial role. Specifically, they observe that the client's characteristics influence auditor technology adoption. In determining the complexity of the audit client, key factors come into play, that is, industry, organizational structure, and IT use.

The client's preference for the auditor's data access (e.g., providing a direct connection to the client's data repository) impacts the adoption of emerging technologies. These client preferences directly influence how the auditor can deploy the emerging technology during the audit and ultimately the diffusion of the emerging technology throughout the audit process and audit firm. Deployment involves the testing, implementation, and its use by the audit team. Deployment necessitates coordination with the client to obtain digital data in the form required by the emerging technology. For example, instead of obtaining printouts of transactions from the client's enterprise resource planning (ERP) for substantive testing, the emerging technology may require a direct connection to the client's ERP for continuous monitoring/assurance. Client data security preferences and digitization capabilities influence auditors' emerging technology deployment. Interviewees in Austin et al. (2021) suggest that auditors and their clients support each other's digital transformation journeys.

Clients can, in turn, set an expectation for their auditors to use innovative technologies with the hope of obtaining additional insight as a byproduct. An auditor participant in Krieger et al. (2021) described how their client pitches necessarily include a discussion of the incremental insights they can provide using advanced analytics. However, this desire by auditors to generate client insights to demonstrate their value should not be the main driving factor for adopting emerging technologies. Buchheit et al. (2020) surveyed 31 US audit partners and one manager who audited private companies. Results suggest that client complexity is central to technology adoption. That is, auditors should ensure that the analytic tools they use and the insights they provide should be in line with the value their clients expect to receive.

Client expectations can also create tensions between the audit client and auditor, which inhibits the adoption of emerging technologies. For example, through interviews with auditors and company managers, Austin et al. (2021) identified a tension between the two parties around audit fees. This tension surrounded the anticipation of reduced audit fees by the audit client and the need for the auditor to recoup costs of adopting the emerging technology. These divergent perspectives breed tension that inhibits the smooth adoption of emerging technologies.

Munoko et al. (2020) address stakeholder tensions arising from the use of emerging technologies on audit engagements. They discuss the possibility of an expectation gap when auditors advertise their use of emerging technologies to test full populations of transactions. The expectations of the client's investors may shift from reasonable (or limited) towards absolute assurance, which is not the objective of external audits. Expectations might also diverge between auditors and other stakeholders when they leverage technology to evaluate nonfinancial information (e.g., disclosures). However, Michael and Dixon (2019) find that leveraging technology to evaluate nonfinancial information narrows the expectations gap because auditors and other stakeholders support the use of technology.

6.1.3 | Business drive to achieve/maintain competitive advantage

Emerging technologies provide opportunities to increase audit efficiency and effectiveness. For example, robotic processing automation (RPA) provides auditors an avenue to automate routine, mechanical and repetitive audit tasks (Moffitt & Vasarhelyi, 2013). To investigate the adoption of RPA in public accounting, Cooper et al. (2019) interviewed 14 national or global RPA leaders across Big 4 accounting firms. Results describe the rapid adoption of technology in the firms. Though they identify no direct impact on audit fees, participants suggest a material increase in audit efficiency and effectiveness postadoption. Drone technology can improve asset measurement, enabling auditors to inspect and verify the existence of hard-to-reach client assets or perform counts of mobile inventory such as livestock (Appelbaum & Nehmer, 2017; Christ et al., 2021). The use of drones can drastically improve audit efficiencies for complex audit asset/inventory inspections. For example, Christ et al. (2021) found that drones' inventory counts reduced inspection time from 681 to 19 h and reduced inventory count errors from 0.15% to 0.03% (Christ et al., 2021).

6.1.4 | Regulation on the adoption of emerging technologies

Uncertainty about regulators' response and acceptance of emerging technologies can hinder its adoption (Dagilienė & Klovienė, 2019). For example, a study of Norwegian heads of audit firms found that the leaders were uncertain about the supervisory inspection authorities' reaction to audit data analytics in auditing and that the firms adopted different technology strategies (Eilifsen et al., 2020). A lack of understanding of the regulators' position and insufficient guidance on technology adoption created hesitance in adopting these technologies. The audit firm leaders reported that regulators' perspective was to inspect completed engagements and then decide whether the technology was appropriate. This uncertainty contributed to the rare adoption of advanced audit analytics in the studied firms.

Through interviews with auditors and company managers, a similar study by Austin et al. (2021) found that lack of accounting regulation on the use of emerging technologies caused "confusion and frustration." For example, the remarks of an auditor during that study demonstrated this confusion: "there may be fear that you'd get punished for doing the analytics because it doesn't tie to the standards. Unless you take something away from the audit, it is just additive. The firm is pushing the use of analytics, but there is still hesitation because of impact on inspections." They also point to the tension between existing audit standards and a growing practice between auditors and company managers. They find that audit firms provide clients with business insights using data analytics, which regulators perceive as a breach of independence, impacting audit quality.

While there is a general requirement by auditing standards for auditors to know available technology-based audit techniques, more specific guidance about which techniques should be learned and adopted by auditors is needed (Appelbaum et al., 2021). For example, the lack of explicit guidance on drones for audit can inhibit its adoption. Despite the drastic reduction in inventory count hours and errors resulting from using drones in place of the traditional audit approaches, Christ et al. (2021) find that audit firms are hesitant to be the first movers in the adoption of drones because of a lack of guidance from regulators. The authors call for regulatory advice in the use of technology-enabled inventory audits. Interestingly, fewer restrictions on emerging technology could also lead to broader adoption. The Federal Aviation Administration relaxed the regulation of drone use resulting in the rapid adoption of the technology (Appelbaum & Nehmer, 2017). Big 4 firms report piloting drones for auditing, although these are not broad adoptions across the firms or their regions, but proof-of-concept (Munoko et al., 2020).

6.2 | Person-specific factors

The audit setting (environment) and the characteristics of the underlying audit tasks play a role in the types of advanced analytics auditors use. However, person-specific characteristics dictate how auditors use them. Teeter et al. (2010) introduced the notion of a remote audit to redefine how auditors view leveraging technology related to nature, timing, extent, and costs of an audit. While focused on internal audit, their framework suggests that firms should consider a holistic, rather than an ad hoc, approach to leverage technology by integrating information and communication technology with analytical procedures auditors already perform. This approach allows auditors to accumulate more persuasive audit evidence. We begin this discussion with a background on two barriers or antecedents to adopting technology in the audit setting—accounting curricula and auditor characteristics.

6.2.1 | Barriers and antecedents to adoption and use of technology

Accounting curricula

Researchers consistently note that accounting curricula lag accounting practice due to complexities in augmenting university course content. The digital transformation process in auditing is no exception. Researchers offer proposals for how to adapt the curriculum.

Coyne et al. (2016) discuss core competencies and suggest curriculum revisions for accounting information systems courses. They suggest that many core competencies are included in current curricula (e.g., drivers of an accounting information system, how the system is protected). Missing components are an understanding of the information lifecycle—how data becomes information, particularly in the era of big data bringing larger volumes and velocity of data, and the technologies of the information system—hardware, software, storage, and services provided. These competencies are central to auditors' ability to converse with IT stakeholders and develop appropriate audit tests. In line with these missing competencies, they suggest accounting information systems courses focus more on these competencies rather than emphasize internal controls (protecting the system) and drivers. Tapis and Priya (2020, p. 133) describe a data analytics course that responds to a call from the Association to Advance Collegiate Schools of Business (AACSB) (*Standard A5*) for "a more holistic approach to teaching and incorporating data analytics into accounting programs." This standard and the proposed course are essential to discuss concerning person-specific factors. Both call for greater emphasis on helping students become more agile and use more critical thinking when interacting with disruptive technology. They propose a mix of practitioner involvement in course delivery and assessing and measuring changes in students' adaptability and agility during the course.

Ozlanski et al. (2020) also focus on disruptive technology and incremental changes to help students anticipate how such technology could influence the audit profession and their work. They describe a stepwise approach whereby students evaluate how an online company is currently disrupting their industry (lending to nontraditional and small businesses) and then apply auditing concepts and theory (e.g., audit evidence, assertions, and analytical procedures). Vincent et al. (2020) focus on a niche type of digital transformation—RPA. This course is technical but includes how to introduce the technology and its benefits to educators and students.

Auditor characteristics

Prior literature on auditors' technology use adopts a version of the Unified Technology Adoption Model (e.g., Venkatesh et al., 2003) to understand technology barriers. Lowe et al. (2018) discuss such use to improve audit quality (see more in Section 7.1). Demand continues to increase among audit firms of all sizes (Big 4 and non-Big 4) for auditors to adopt and use disruptive technology. The interest in auditor technology-specific competence is also prevalent in emerging economies (e.g., Tarek et al., 2017).

Diaz and Loraas (2010) examined postadoption behavior. This approach is essential because, as noted in Salijeni et al. (2021), digital transformation has reconstructed the market for audit services. However, little attention has been paid to "the performative nature of such technologies and how their properties may shape the dynamics of technological change" (Salijeni et al., 2021, p. 531).

Diaz and Loraas (2010) conducted a two-stage experiment with 69 senior accounting students who completed a 10-week busy season internship in the United States. Their conceptual model informed the experiment on technology adoption. A central finding is that the difficulty required to learn technology impacts junior auditors' attitudes and perceptions of anticipatory affect, time budget pressure and social influence. Payne and Curtis (2017) experimented with 104 auditors at varying experience levels and across several accounting firms. Results suggest that providing timely (e.g., before busy season) technology training is a plausible intervention to mitigate reticence to engage with technology. As noted in Diaz and Loraas (2010), results also suggest that ease of use impacts intentions to use technology. Further, individual factors such as lower confidence in memory recall, lower task-specific experience, gender, and experience level in the firm increased the auditors' intentions to train on technology use. These findings complement Salijeni et al. (2021), who find that big data analytics increase the "evidential scope" of audits. The following discussion summarizes the research examing person-specific factors by type of data analytic.

6.2.2 | Descriptive analytics

Much of the literature focuses on descriptive analytics, that is, the less complex type of digital transformation. This study focuses on data visualization and population testing. Hamdam et al. (2021) reviewed prior literature to develop a conceptual framework to model the cognitive process that could influence auditors' decisions in a big data environment. The framework considers the intersections of descriptive-analytic tools like data visualization, data processing modes, the complexity of the underlying audit task and auditors' judgment and decision-making. The premise is that the appropriate integration of data visualization into audit tasks will improve decision-making. Task complexity and information overload associated with the voluminous amount of data required to enable the analytic tools may limit these improvements. Many of these theoretical propositions are discussed in the literature that follows.

As previously discussed, Austin et al. (2021) interviewed auditors and audit stakeholders. Relevant to person-specific factors, their study examines how these stakeholders use data analytics and its influence on their interactions. A primary finding is that auditors "strategically leverage data analytics to provide clients with business-related insights" (Austin et al., 2021, p. 1892). When focused on the question "what happened?" auditors must access large volumes of client data. Such access enables diagnostic and predictive analytics, but as the regulator participants indicated, this could create independence concerns for auditors. Both the auditor and manager interviewees specifically highlighted descriptive-type analytics in use. For example, they mentioned using data analytics for pattern identification and analysis, evaluating anomalies and outliers, and using visualization tools (e.g., PowerBI, Tableu) to graphically describe and communicate their current financial performance to clients. One auditor participant described their use of data analytics as follows (Austin et al., 2021, p. 1903):

> [As auditors], we're not just looking for unusual transactions or unusual results, but a combination of unusual transactions. It's about connecting the dots. And it's hard for humans to connect those dots. Previously, auditors could connect two or three different pieces of information, but [with data analytics] you can connect five dots and when you look at the pattern, now some-thing emerges we hadn't seen before.

A central concern with voluminous amounts of data is information overload (e.g., No et al., 2019). However, the risk does not appear to outweigh the benefits. Findings in Austin et al. (2021) are consistent with and contribute to Salijeni et al. (2021).

Like Austin et al. (2021), Salijeni et al. (2021) evaluated Big 4 and mid-tier audit firms' publications and reports on the use of digital transformation technology and interviews with 25 practitioners, including auditors and regulators in Europe. A key finding focuses on the benefits of “visualization dashboards.” When using visualizations, auditors are better able to assess their clients' operations and generate more persuasive audit evidence. This finding contrasts with prior literature suggesting visualizations are more like job aids (e.g., Solomon & Trotman, 2003) rather than providing incremental knowledge that improves audit outcomes. As an added benefit, visualizations help auditors better manage the flow of tasks on engagements.

A common use of descriptive-analytic tools in audits enables population testing rather than evaluating samples. As we later discuss, auditors' use of the output of those tools could also facilitate diagnostic and predictive analytics. Cao et al. (2021) conduct an experiment with 140 auditors at the senior auditor level and above from Big 4 firms in Taiwan. They examine whether mindset (e.g., fixed or growth) moderates the effect of inspection risk (the likelihood an audit engagement will be selected for regulatory inspection) on auditors' reliance on data analytic tools. The data analytic tool is a visualization that compares the client's sales transactions with Google Trends Index values for the client's potential customers' searches of their products. The goal is to identify any anomalies. They find that when inspection risk is high, auditors rely less on the data analytic tools when prompted with a fixed mindset (a belief that one's ability is fixed). Reliance increases when prompted with a growth mindset (a belief that one's ability is malleable).

Emett et al. (2021) conduct two experiments examining external reviewers' perceptions of auditors' use of data analytic tools. Participants are 60 audit partners and senior managers (Experiment 1) and 98 experienced auditors (Experiment 2) with external review experience who assume the role of Association of International Certified Professional Accountants (AICPA) peer reviewers.[7] The authors manipulate whether the engagement team under review used traditional audit procedures or data analytic tools. Results in Experiment 1 suggest that external reviewers perceive data analytic tools as lower quality than traditional audit procedures because they perceive that automating such tools requires less auditor effort. In Experiment 2, the study introduces a priming intervention whereby participants first read a statement from the global head of audit that emphasizes either audit effort or audit execution. Results suggest that the audit effort prime is associated with similar outcomes as Experiment 1;

the use of data analytic tools was perceived as relatively lower quality. When primed with the audit execution intervention, the reviewers perceived the two audit approaches to be similar in quality. The results complement Cao et al. (2021) and other research (e.g., Brown-Liburd, Brown-Liburd, et al., 2021; Brown-Liburd, Brazel, et al., 2021) that suggests stakeholder views (e.g., peer reviewers, regulators) influence auditors' willingness to adopt technology.

Witte-Fairfield et al. (2021) interviewed 28 senior auditors employed by regional and national firms in the United States to understand the implications of investments in technology-based audit tools.[8] The findings emphasize that audit firm culture, engagement budgets, and training drive behavior, complementing Diaz and Loraas (2010) and Payne and Curtis (2017).

6.2.3 | Diagnostic analytics

As previously mentioned, practicing auditors also use population testing as a dual-purpose test of not only what happened but also why. Hamdam et al. (2021) developed a conceptual framework that suggests task complexity moderates the effectiveness of technology use in the audit. This relation is particularly germane to diagnostic analytics because testing the full population rather than a sample could increase the complexity of the diagnostic task when voluminous anomalies could be identified. The number of anomalies could be a multiplier of the size of traditional audit samples (e.g., 25 transactions). The findings of Salijeni et al. (2021) are also applicable because the auditor's approach to testing anomalies that result from population testing could differ. That is, do auditors attempt to evaluate all anomalies or take a sample? Either approach could influence the quality of auditor judgments as a sample would be based on known “potential” exceptions, many of which are identified as false-positives when evaluated further. In Austin et al. (2021), the auditor and manager participants also mentioned diagnostic analytic tools. They mentioned using data analytics, in conjunction with data from various sources, based on statistical tools and predictive models, to understand past performance.

At least four contemporaneous studies use external perceptions of auditors' population testing as a diagnostic analytic tool. As previously described Emett et al. (2021) used auditors with external review experience as participants rather than jurors. The three other studies use the auditor litigation setting with jury-eligible MTurk workers as participants.[9]

Kipp et al. (2020) examine the combined effects of auditors' procedures used to follow up on exceptions identified by a data analytic tool and the lack of an audit standard governing the use of data analytics on jurors' assessments of auditor negligence. The underlying theory is algorithm aversion, which suggests individuals will be more likely to discount computer-generated advice or evidence more heavily than human advice or evidence. Otherwise, the advice (evidence) is identical (e.g., Dietvorst et al., 2015). Participants are juror-eligible individuals. Consistent with algorithm aversion, results suggest that jurors assess higher negligence when auditors use AI to select a sample of exceptions identified by a separate tool to evaluate further versus when a human selects the sample of follow-up items. Participants perceived auditors more as the cause of the audit failure and the failure to be more foreseeable when they used AI. The results also suggest an interactive effect. The use of AI to select exceptions and lack of analytics-specific standards results in the highest negligence verdicts.

Motivated by auditors' perception that audit data analytics would increase their legal liability because stakeholders may perceive a higher than reasonable level of assurance, Barr-Pulliam, Brown-Liburd, et al. (2021) also examine juror perceptions. The study specifically examines how the auditor's testing methodology (population testing via audit data analytics or traditional sampling) and the type of internal control opinion issued (unqualified or adverse) affect jurors' perceptions of auditor negligence. The study includes multiple experiments, focusing on the sufficiency and appropriateness of audit evidence and the signals provided by the audit methodology (a private signal) and the internal control opinion (a public signal). The description of the audit data analytic tools informs the jurors that auditors tested the entire population of revenue transactions for the client and identified 5% as exceptions from which they could then evaluate "true" exceptions further. This characterization suggests a diagnostic rather than descriptive use of the technology in the audit. The findings suggest that when auditors issue an unqualified internal control opinion, jurors are more likely to find auditors guilty of negligence when they employ statistical sampling than audit data analytics. However, when auditors send a "signal" of potential financial reporting problems by issuing an adverse internal control opinion, jurors attribute less blame to auditors and more blame to management and the investor (plaintiff) when an audit failure occurs. A supplemental experiment suggests that jurors perceive the auditors' use of data analytic tools as an indicator of higher audit quality and are less likely to find them guilty of negligence. Jurors do not differentially perceive the level of assurance across methods.

Lowe et al. (2021) conduct an experiment similar to Barr-Pulliam, Brazel, et al. (2021) and Kipp et al. (2020). They manipulate whether the audit is driven by data or human (professional) judgment and whether the auditor's data analytic tools identified and correctly flagged materially misstated transactions for further testing. Lowe et al. (2021) characterize their data analytic tool as advanced use of the technology and consider it diagnostic rather than descriptive. The study combines counterfactual reasoning and persuasion theories to develop predictions. The theories assert that the more an adverse event such as an audit failure is perceived as avoidable, jurors will more readily envision counterfactual alternatives (e.g., Reffett, 2010). They observe greater counterfactual reasoning when the transactions underlying the material misstatement were flagged as anomalies versus when they were not. The results also suggest that jurors interpret this message more cognitively (rather than affective manner) when auditors emphasize a data-driven audit approach versus human (professional) judgment.

6.2.4 | Predictive analytics

Most of the prior research we identified focuses on descriptive and diagnostic analytics. The conceptual model developed in Salijeni et al. (2021) and participants' sentiments in Austin et al. (2021) have implications for, but we identified few studies incorporating predictive analytics.

Commerford et al. (2021) use a specific individual characteristic—algorithm aversion—to examine how auditors respond to contradictory evidence from an analytic tool. Participants are 170 audit seniors with approximately 4 years of experience and represent two Big 4 firms. The experiment manipulates the source of audit firm-provided evidence used to evaluate a complex estimate (human vs. AI system) and the nature of management's inputs and assumptions (subjective vs. objective). The task in this study is predictive, rather than diagnostic, because either an audit firm employed specialist (human) or the firm's proprietary AI system develops an expectation for the client's allowance for loan loss reserves. Focusing on the subjective or objective nature of the inputs and assumptions allows the auditor to evaluate "what will happen" and how different their independent estimate of the loan loss reserve is, compared to management's reported value. Further, a fundamental premise of algorithm aversion in the audit setting is that discounting one piece of audit evidence results in the auditor placing more weight on competing pieces of information. Auditors who receive contradictory evidence from the AI system propose smaller adjustments to management's initial estimate, mainly when the underlying inputs and assumptions are objective.

Bakarich and O'Brien (2021) surveyed 172 public accounting professionals representing multiple US firms, service lines, and experience levels. Results from 90 completed surveys are used to evaluate perceptions of and the extent that AI use—specifically RPA and Machine Learning (ML)—within the respondent's audit firm. These two forms of AI are touted as most used by audit firms. We categorize this study as a predictive analytic tool because the capabilities of AI and machine learning emphasize automating business processes (likely more descriptive and diagnostic), gaining insight through data analysis (predictive and potentially prescriptive analytics) and engaging with customers and employees (enabling predictive and prescriptive analytics). The survey results suggest that the actual use of both forms of AI is less prevalent than suggested by the firms' external communication. Results also suggest that clients are not using the technologies as frequently. Larger firms (e.g., Big 4) are more likely to have the resources to train and implement these technologies at scale. Thus, a critical driver of use is training on the tools, though participants perceive significant upside for the accounting profession if adopted. No differences were identified across service lines within-firm size. Unsurprisingly, tenure in the firm was negatively associated with self-reported expertise with AI technology.

Overall, prior research insufficiently addresses how data analytic tools impact auditor judgment and decision-making. Despite the benefits of incorporating data analytics, the analysis and interpretation of the data output may be challenging for auditors since they would need to be proficient at pattern recognition and critical thinking. With many types of data analytics, auditors' focus shifts from errors in the sample to anomalies in data patterns about the population (Brown-Liburd et al., 2015; Earley, 2015). Research examining auditor judgment finds that auditors are not very effective at recognizing patterns data (e.g., Asare et al., 2000; Bierstaker et al., 1999). Rose et al. (2017) find that visualizations are less effective when viewed before more traditional audit evidence. Koreff (2021) extends this study. The study examines whether auditor judgment and decision-making differ based on the type of data analytic model (anomaly vs. predictive) and type of data analyzed (financial vs. nonfinancial) in an analytical procedures task. Results suggest that auditors increase proposed audit hours when financial data is analyzed using predictive models. Alternatively, auditors increase proposed audit hours more when anomaly models analyze nonfinancial data. Together, findings suggest that data analytics with different inputs may not uniformly impact auditor judgment and decision making.

Because data analytics often involves full population testing or incorporating Big Data into analyses, there is a risk that auditors will experience information processing weakness and cognitive limitations (e.g., information overload) when analyzing and interpreting output from data analytic tools and techniques (Brown-Liburd et al., 2015). Thus, research examining methodologies that help auditors organize and appropriately apply the information generated from data analytics can minimize judgment errors. No et al. (2019) propose a systematic approach for auditors to use data analytics in the audit data selection process. Specifically, they develop a Multidimensional Audit Data Selection (MADS) framework that addresses the impracticality auditors face in resolving a potentially large number of outliers resulting from full population testing. The framework uses a multistep process to assess notable items or outliers to determine whether they contain a higher risk of material misstatement. First, data analytics is used to identify anomalies from the entire population and then prioritization methodologies are applied to the identified anomalies. As a result of applying this framework, auditors can focus on items with a higher risk of material misstatement, ultimately enhancing the effectiveness of the audit.

Wongpinunwatana et al. (2000) experimentally investigate how the AI technique used impacts cognitive information processing. The study uses auditing students as a proxy for novice auditors and manipulates the type of task (structured [internal control assessment] vs. unstructured [going concern assessment]) and the type of AI system (rules vs. cased based reasoning) to examine participants' problem-solving accuracy and their certainty that their solution was correct. Expectations are developed based on the task-technology fit model. The authors hypothesize that for a structured task, accuracy is greater using rules-based versus case-based reasoning (results were marginally significant at 0.10 level). Whereas for unstructured tasks, AI techniques utilizing case-based versus rules-based reasoning result in greater accuracy (results were not significant). The lack of significant findings may be due to using undergraduate students studying auditing to perform complex tasks. There was marginal support for the certainty of solution such that certainty is higher for structured tasks when a rules-based versus case-based reasoning AI technique is used. In contrast, certainty is higher for unstructured tasks when case-based versus rules-based reasoning AI is used. While the results of this study were mixed, it does illustrate the importance of identifying interventions that potentially help auditors improve their judgment in a data analytic environment. Barr-Pulliam, Brazel, et al. (2021) demonstrate that higher levels of false positives associated with data analytics can negatively influence the extent to which auditors exhibit professional skepticism. However, this negative outcome can be mitigated by consistently rewarding auditors for exhibiting appropriate skepticism.

6.3 | Task-specific factors

Audit research indicates that auditors face tasks that have significant variations in the level of complexity (e.g., Abdolmohammadi, 1999; Abdolmohammadi & Wright, 1987; Bonner, 2008). This study defines task complexity in terms of the structure of the task (i.e., structured, semistructured, and unstructured). Prior research examining the effect of task complexity on auditor judgments finds that judgment quality is impacted by the level of task complexity (e.g., Bonner, 2008; Tan & Kao, 1999). For example, increases in task complexity may result in knowledge being inaccurately applied, which can negatively impact judgment performance (Bonner, 2008). Recognizing the increasing importance of emerging technology in the audit process (Wang & Cuthbertson, 2015), it is essential to understand how use of these tools interacts with task complexity to impact judgment quality. For example, the use of a more advanced data analytic technique such as clustering entails analysis of larger data sets to identify patterns in the data signaling potentially higher risk areas that the auditor should further investigate. The unstructured nature of this task may increase complexity because the auditor must process a higher number of information cues (e.g., larger data set), combine the information in an unspecified way (e.g., identify patterns), or adapt to changes in required actions or information cues (e.g., identify higher risk areas) (Wood, 1986). The type of data analytic tool or technique used potentially adds an increased level of complexity when used in the performance of unstructured tasks.[10] The following discussion summarizes the research examing task-specific factors by type of data analytic.

6.3.1 | Descriptive analytics

A typical audit task performed using descriptive analytics is analytical procedures, a task that research has found auditors to be deficient in performing; Messier et al. (2013) review literature on analytical procedures. Rozario et al. (2021) examine consumer-generated tweets about purchases (interest) and sentiment to determine whether auditors can use these tweets to assess revenue risk in the planning stage of the audit. Using a database of consumer-generated tweets for companies in consumer-facing industries, they find that, relative to a benchmark model, Twitter consumer interest can improve analytical procedures' prediction and error detection ability. Given prior research documenting deficiencies in auditors' performance of analytical procedures, Rozario et al.'s (2021) findings provide a promising approach using data analytics. Indeed, Trompeter and Wright (2010) report that auditors perform better benchmarking and incorporate relevant information resulting from technology.

A primary benefit of data analytics is increased audit quality (e.g., Earley, 2015; Wang & Cuthbertson, 2015). How stakeholders perceive auditors' use of advanced technology potentially impacts their perceptions of audit and financial reporting quality and, in turn, their perception of the level of assurance provided by data analytic techniques. Ballou et al. (2021) examine the perceptions of key stakeholders when auditors perform full population testing and predictive modeling data analytics-based procedures relative to traditional sample-based substantive testing. They find that investors' willingness to invest is unaffected by the use of data analytic techniques. The perception of peer reviewers was also unaffected by whether data analytic techniques influence the quality of audit procedures or their ability to detect material misstatements. In contrast to investors, peer reviewers expressed apprehension about the reliability of data used in predictive modeling. Jurors were less likely to hold auditors liable and viewed audit procedures as more justifiable when auditors used population testing.

As previously noted, Emett et al. (2021) find that external reviewers perceive audit procedures using data analytic techniques as lower quality than traditional audit procedures. This result contrasts with Ballou et al.'s (2021) findings that peer reviewers' perceptions of audit quality are not affected by auditors' data analytics use. Emett et al. (2021) conduct a second experiment to evaluate an intervention to mitigate the effort heuristic. Results show that priming participants to consider how effort does not always improve quality appears to mitigate the perceptions identified in the first experiment.

6.3.2 | Diagnostic analytics

Accounting researchers have used various technological approaches to demonstrate diagnostic analytics for various phases of the audit process, such as risk assessment and substantive tests. For example, audit firms deploy AI in their assurance and advisory practices (Munoko et al., 2020). AI allows auditors to analyze large data sets to detect anomalies and identify insights, patterns, and relationships that would not be readily apparent to auditors when using traditional audit approaches. Augmented AI systems can be used to conduct diagnostic analytics because this type of AI exhibits "analytical intelligence that enables the AI to learn from data and process information for problem-solving" (Munoko et al., 2020).[11] As a result, AI is an emerging audit area of research, ranging from the use of drones to RPA to contract analytics.

AI-enabled techniques such as natural language processing can be used to analyze contracts for unusual terms or clauses that require additional consideration. Auditors can focus on the reasonability of the key contract terms and understand how the contract fits within the larger context of the business. Zhaokai and Moffitt (2019) propose and test a contract analytic framework that uses natural language processing and text mining techniques to facilitate effective and efficient audit analyses on full populations of contracts. They identify audit procedures related to contracts based on audit standards (e.g., AS No. 5; AS No. 14; AU 342) that can be improved or automated utilizing the framework.[12] Additionally, they test the framework's effectiveness on a set of insurance contracts and assess the feasibility of generating audit evidence from the entire population of contracts. Results indicate that the framework is an effective tool to help auditors perform full population examination of contracts and related audit tasks.

Audit firms invest in advanced automation technologies to replace traditional labor-intensive, time-consuming audit procedures (e.g., Huang & Vasarhelyi, 2019). For audit procedures that are well-defined, highly repetitive, predictable and involve multisteps across multiple systems, RPA is ideal (e.g., Huang & Vasarhelyi, 2019). RPA is an advanced automation technology that has received broad interest from auditing firms. As such, accounting research has begun exploring how RPA can be applied in audit practice (e.g., Eulerich et al., 2021). Huang and Vasarhelyi (2019) propose an RPA framework for audit engagements. The study describes the pilot implementation in conjunction with an accounting firm. The focus was on automating the confirmation process using the framework. The outputs of the RPA pilot project were independently compared with the manual process by the CPA firm, and the results demonstrated the feasibility of the framework and the usefulness of RPA in auditing.

Eulerich et al. (2021) also developed and validated a framework to help auditors decide what activities to automate using RPA. The framework draws upon sociotechnical systems theory and uses a design science approach to develop practical guidance. The study uses interviews and surveys of experienced internal and external auditors and case studies to validate the framework.[13] Both internal and external auditor interviewees indicated that their organizations do not have RPA frameworks to guide the automation of audit tasks and agreed that a framework is necessary and would be helpful. Participants viewed the proposed framework as valuable and relevant.

When performing diagnostic analytics, auditors can combine company and exogenous data to gain deeper insights. Incorporating exogenous data (i.e., weather data) into statistical models, Yoon et al. (2021) demonstrate how exogenous data improves the effectiveness of substantive analytical procedures in the audit of revenue. Specifically, using the US data of a publicly held multilocation retail company, they use multivariate regressions to examine whether weather variables accurately predict daily store sales on a regional basis and thus, can serve to enhance expectations. Overall, their results show that weather indicators (e.g., temperature, humidity) explain the incremental value provided by weather indicators, but the value is limited and dependent upon the season and store region. For example, in the spring season prediction accuracy is enhanced for many regions, whereas in the summer prediction accuracy is enhanced only for only a few stores in the southern region. These results highlight the importance of carefully evaluating how the exogenous data of interest links to financial accounts.

6.3.3 | Predictive analytics

The studies discussed in this section provide insight into the capacity for data analytics to enhance audit procedures and how the use of various types of data analytics, compared to traditional audit procedures, improves the efficiency and effectiveness of the audit process and impacts stakeholder perceptions about audit quality.

Advances in AI have broadened the scope of analyses that can be performed with predictive analytics. Accounting research has begun to examine how predictive analytical techniques can enhance financial reporting and audit quality. For example, assessing management's estimates is a key and complex area that entails significant management judgment. Auditors could use machine learning to develop independent estimates to compare to management's estimates. Ding et al. (2020) demonstrate the feasibility of this type of model using publicly available annual statutory reports of US-based property-casualty insurance companies to predict loss estimates. Findings suggest that the machine learning-generated insurance loss estimates are more accurate than the loss estimates reported in the statutory reports in all business lines examined except for one. The difference is attributed to the fact that managerial incentives motivate managers to report biased estimates. One benefit of this model is that it can be retrained every year based on actual loss data.

AI-based systems leverage machine learning for various tasks. One example is to analyze data using tone and sentiment. Another is to classify data into relevant factors, such as potential risks that have been used to predict fraudulent firms (e.g., Goel & Gangolly, 2012; Goel & Uzuner, 2016). Further, such systems have been used to flag questionable financial disclosures (e.g., Humphreys et al., 2011).[14]

Munoko et al. (2020) use an approach designed to identify fraud risk cues *before* the audited financial statements are publicly available. The study describes and validates a machine learning and natural language processing framework for analyzing corporate digital communication to detect collusive fraud risk within an organization. The framework draws on established fraud theories to hypothesize that fraud risk cues can be detected by analyzing the temporal changes of individuals' sentiments, emotions, topics, and communication patterns via digital communications. A panel of forensic experts who are US Certified Public Accountants (CPAs) with a high degree of technical accounting skills express fraud risk assessments consistent with the machine learning framework.

Process mining is a technique used to systematically analyze the entire population of event logs recorded in a company's IT system (e.g., Jans et al., 2013; 2014). Research examining the application of process mining to audit tasks is emerging and demonstrates that it improves the evaluation of the effectiveness of internal controls over financial reporting (Chiu & Jans, 2019; Duan, 2021) and other analytic procedures (e.g., Jans et al., 2014). Indeed, Jans et al. (2013) argue that internal and external auditors should leverage process mining in the audit process. Specifically, auditors can analyze the entire population of data, including meta data, which is independent of the data entered into the system by the client, conduct a more effective control risk assessment, and discover how business processes flow.

Chiu and Jans (2019) demonstrate how process mining can assist auditors in evaluating the effectiveness of internal controls using actual event log data. The results from the case study demonstrate that auditors can use process mining to perform variant analysis to understand deviations from the organization's expected business processes fully. Additionally, auditors can detect potential control risks, ineffective controls, and inefficient processes. Duan (2021) incorporates process mining and machine learning algorithms to develop a predictive analytical model to evaluate internal control. The model utilizes process mining techniques to identify deviations from the established business process and assesses the controls associated with identified deviations. The model then applies machine learning algorithms to determine the high-risk transactions for further investigation. The model is validated using actual event log data. Results indicate that the model systematically evaluates controls, identifies ineffective and missing controls and effectively directs the investigation to high-risk areas. The approach substantially reduces manual control testing and enhances overall audit quality by more precisely assessing control risk and the level of substantive testing.

To perform analytical procedures, Jans et al. (2014) applied process mining to the procurement data from a leading global bank. The results identified several anomalous transactions such as payments made without approval, violations of segregation of duty-related internal controls, and violations of company-specific internal control procedures. The bank's internal auditors did not detect anomalous transactions using traditional audit procedures when examining the same transactions.

While the above studies highlight the beneficial uses of predictive analytics in the audit process, Ballou et al. (2021) find stakeholders views of predictive analytics as enhancing audit quality are mixed. Investors' view predictive modeling more favorably than full population testing and traditional sample-based substantive testing when the risk of material misstatement is high. In contrast to investors, peer reviewers expressed apprehension about the reliability of data used in predictive modeling. Further, jurors were less likely to hold auditors liable and viewed audit procedures as more justifiable when auditors used population testing versus predictive modeling.

7 | EMERGING TECHNOLOGY PRESENTING FUTURE ASSURANCE OPPORTUNITIES FOR AUDITORS

The fit of emerging technology with professional standards is a factor that auditors consider when determining whether to adopt an emerging technology (Krieger et al., 2021). New regulations can drive the adoption of emerging technology. For example, AICPA standards on audit evidence (AU-C 500), identifying, assessing, and responding to the risks of material misstatement (AU-C 315), and analytical procedures (AU-C 520) require or call for the consideration of exogenous information collected using emerging technologies such as bots.

During the audit, big data and AI can provide descriptive, predictive, diagnostic, and prescriptive insights. Concerns around the use of data have driven regulation on data use in auditing. An example of such standards is *The Auditor's Responses to Assessed Risks* (ISA 330) that requires auditors to consider the integrity and reliability of the data source.

7.1 | Continuous auditing (CA; assurance) and continuous monitoring (CM)

The concept of CM and CA (also referred to as continuous assurance) has been in the accounting literature for over three decades (Sun et al., 2015). CM systems were initially designed to compare transactions to data-based analytics derived from ratio and trend analysis of historical data (Vasarhelyi & Halper, 2018). The system alerts management or internal auditors when deviations from established thresholds occur (Appelbaum et al., 2021). CM is generally associated with continuous monitoring of controls (CCM) and is a methodology that allows management to review controls to identify deviations from established procedures continuously and proactively. The passage of the Sarbanes-Oxley Act in the United States, specifically Section 404 Internal Controls, amplified the importance of monitoring financial reporting controls, and auditors are required to attest to the effectiveness of these controls. Research on CCM primarily focuses on the role of internal audit. Alles et al. (2006) present a pilot implementation of CM of business process controls with a formalization and re-engineering of audit procedures to enable the system's CA.[15] The US internal IT audit department of Siemens Corporation undertook the pilot implementation, which allowed the researchers access to real-world audit programs and internal auditors. The pilot study provided insights into the challenges, constraints, and opportunities related to the implementation of CA. One challenge is transforming manual audit procedures where auditors use their experience and exercise judgment into procedures that a CA system can automatically perform. Another challenge is a large number of exceptions, which, as previously discussed, could overwhelm auditors (Alles et al., 2006).

CA enables auditors to gather process data that support audit activities continuously. The emergence of more advanced technologies and regulators' and standards setters' support for continuous assurance have renewed interest in CA (Koskivaara & Back, 2007). Vasarhelyi et al. (2004)[16] note that CA is increasingly impacting the audit profession and that approximately 80% of US companies either use or plan to use CA techniques. Interest in CA research is increasing, especially in enabling technologies.[17] Internationally, the view of CA is also positive. For example, Tiberius and Hirth (2019) find that German auditors expect the annual external audit to evolve toward a more continuous auditing approach.

The concepts of CM and CA have evolved over the last three decades due to emerging technology. Such technologies include the Internet of Things (IoT), enabling internal/external auditors to continuously monitor company assets' performance. IoT is the interconnectedness of devices over the Internet. It allows these devices to report on their activities autonomously (e.g., manufacturing plants reporting on the number of manufactured items). Other enabling emerging technologies for CA/CM include AI, big data cloud computing, and Blockchain. We discuss these technologies below, describing how they can facilitate continuous monitoring and auditing.

7.2 | AI

AI is the ability of technology to mimic human cognitive skills, such as the ability to reason, see, converse in human-understandable language and perform physical tasks (Munoko et al., 2020). Accounting researchers and professionals have examined how AI can enhance the accounting function since the early 1980s (Sutton et al., 2016). In the 1980s, developing expert systems able to augment the judgment of junior (less experienced) auditors was an interest. These expert systems were built using the knowledge of more experienced accountants. Accounting research on AI slowed down in the 1990s (Sutton et al., 2016) due to technical limitations. Recent interest in AI has spiked, given advancements in computing speeds, computing storage, and robust AI/machine learning model developments. Increasingly, accounting researchers are revisiting previous research on AI for assurance and beginning to take a futuristic approach to adopt AI to enhance the assurance profession. AI can assist in automating mechanical tasks performed by auditors; furthermore, current AI systems exhibit more intuitive intelligence. Auditors can use AI to perform prescriptive/predictive/diagnostic tasks, such as risk assessments and testing transactions. Additionally, auditors can use AI to implement a continuous assurance system to monitor clients' internal controls and flag anomalies.

For example, through questionnaires, Munoko et al. (2020) capture auditors' anticipation to use AI for monitoring and evaluating clients' internal controls within the next 2 years.

Law and Shen (2021) examine job postings for accounting firms between 2010 and 2019. They search and categorize these postings at the office level based on AI skills mentioned in their list of preferred candidate characteristics. They find that relative to audit offices that do not have postings including preferred AI skills, those requiring such skills experience an increase in the number of audit-related jobs. These effects are stronger when the office is located in a suburban area and has more jobs that AI could replace. Results also suggest that AI implementation in the firm leads to an upskilled workforce over time. However, these improvements in office-level expertise and operational efficiency are not associated with a decrease in audit and tax fees. The improvement is associated with a lower percentage of clients with restatements and less audit lag.

Rozario and Zhang (2021) explore whether the implementation of AI, vis-à-vis machine learning, in firms' operations is associated with improvements in internal information quality. They use management's earnings forecasts to proxy for information quality. For nontechnology companies that have implemented AI, the results suggest that management earnings forecasts are more accurate postimplementation. This improvement in accuracy resulted in better initial forecasts than the last forecast when AI had not been implemented.

7.3 | Big data

Increasing use of the Internet and other digital technologies has resulted in large amounts of data that may be informative. However, making sense of big data requires sophisticated analytic tools to draw valuable insights from these large data sets. Examples of these data sets include exogenous data such as location, social media, IoT, weather data, sales data, and online reviews (Brown-Liburd & Vasarhelyi, 2015). Due to the mechanical and analytical effort needed to analyze large data sets, accounting researchers and professionals continue to innovate and explore new ways to apply big data to accounting.

7.4 | Cloud computing and cybersecurity

Reliance on companies and auditors generating, storing, and analyzing data over the Internet has increased. Costs to store data via the cloud continue to decline relative to purchasing hardware permitting onsite storage of data. However, the increased reliance on these cloud-based platforms created an emerging risk—cybersecurity. To address these risks in their firms and the risk posed to their clients, auditors readily rely on experts with backgrounds in computer science, engineering, and related fields (e.g., Bauer et al., 2019).

Internal auditors provide assurance within companies to help management manage existing and emerging risks by evaluating internal controls focused on cyber security risks (e.g., Kahyaoglu & Caliyurt, 2018). External auditors should evaluate and document these cybersecurity risks as part of their risk assessments of the clients (Hamm, 2019). Further, this evaluation of clients' cyber security risks provides an opportunity for auditors to offer separate assurance services, where they do not violate auditor independence rules, to assuage management's concerns over these risks.

7.5 | Blockchain

Another emerging technology within the last decade that has a potentially significant impact on assurance is Blockchain. Blockchain is a technology that provides a decentralized public ledger for capturing transactions among parties, creating what can be an immutable record. Interest in blockchain technology has increased due to businesses' recent and rapid adoption of the technology. Blockchain has also captured the interest of auditors as they seek to understand how the technology can be used as a secure and reliable way of digitally recording transactions.[18]

Rozario and Vasarhelyi (2018) evaluate the use of blockchain-based smart contracts. The findings suggest that smart contracts could significantly influence financial statement audits' nature and outcomes because smart contracts permit autonomous execution of some audit procedures, as well as the results of those procedures. The authors further suggest that blockchain-based smart contracts could be appended to data analytics and CA tools.

7.6 | Summary and opportunities

A client's business environment can also drive the adoption of emerging technologies by the auditor. For example, companies' business cyber security concerns may lead them to use more secure frameworks such as adopting blockchain technology (Demirkan et al., 2020). Lastly, regulators can use emerging technology to evaluate auditor compliance with standards. For example, regulators may use blockchain to manage the aggregation, reporting and sharing of practitioner misconduct issues among various interested parties (Sheldon, 2018, 2021). Since audit standards require auditors to evaluate the relevance and reliability of data (e.g., ISA 500, *Audit Evidence*), audit firms will need to develop expertise on assuring technologies, for example, cybersecurity, blockchain, and big data. Beyond its data reliability benefit, blockchain facilitates the trading of most cryptocurrencies and initial coin offerings that finance new ventures. These client innovation endeavors, especially for technology industry clients and new ventures, drive the auditor's requirement to understand and embrace these technologies (Lombardi et al., 2021). These endeavors also call for new Information Technology General Control (ITGC) considerations when auditors rely on these technologies for audit evidence (Sheldon, 2019; Vincent et al., 2020).

8 | FUTURE RESEARCH DIRECTIONS

This section provides recommendations for future research. We classify the proposed research questions as impacting environmental, person- or task-specific factors.

8.1 | Environmental factors

RQ1. The COVID-19 pandemic dramatically changed how auditors perform their daily audit tasks—including interactions with clients and team members within the firm (see also Bauer et al., 2021). How has the pandemic accelerated or inhibited the digital transformation journey? How prepared were firms to adapt to virtual work environments? Are there differences in audit quality provided during the pandemic across firm sizes?

RQ2. Future researchers would benefit from a continued surveys of practitioners. The findings could inform the IAASB and other standards setters in evaluating the need for audit and financial reporting standards that reflect the current use of technology. Some potential focus areas include (see also Gauthier & Brender, 2021):
  i. What are firms' inhibitors and accelerants of emerging technology adoption?
  ii. What audit standards encourage/inhibit the adoption of emerging technologies?
  iii. Given the regional differences in emerging technology adoption, how can global regulators enhance audit standards?
  iv. What new audit assertions should be introduced, and what standards should be augmented in light of emerging technology?
  v. What IT General Controls should be introduced, and which should be augmented in light of emerging technology?
  vi. What gaps exist between stakeholders (auditors, clients, and shareholders)?

RQ3. Few studies have examined technological advances in Non-Big 4 firms resulting in limited insight into how they leverage data analytics. What is the potential impact on audit quality across the profession (Munoko et al., 2020)?

RQ4. Brown-Liburd et al. (2015) find that data analytic techniques and tools are well established in other industries (e.g., insurance, healthcare) as compared to the audit profession. What knowledge from these industries can be transferred to inform the use of these tools in the audit profession? Related questions include:
  i. What environmental factors influence auditors' adoption of emerging technology (e.g., client, competition, regional factors, or regulation)?
  ii. What are the perceived implications for audit quality when auditors adopt an emerging technology?

RQ5. Audit firms communicate the benefits of audit data analytics to mitigate shareholder perceptions that data analytics increases the level of assurance provided. Using the framework developed by Alles and Gray (2016) to model the audit process, future research could evaluate whether the expectation gap between auditors and stakeholders is mitigated or exacerbated when the auditors use advanced data analytics.

RQ6. Pimentel et al. (2021) suggest that cryptocurrencies and emerging technology such as blockchain introduce “novel, technically sophisticated, and risky propositions that auditors are unequipped to handle” (p. 61). Future research could examine assertions noted in Pimentel et al. (2021) by evaluating the core competencies needed to provide assurance to clients holding cryptocurrencies. What knowledge about other technologies or complex estimates can be applied to developing assurance offerings?

8.2 | Person-specific factors

RQ7. Few studies have examined the impact of more complex systems on auditor judgment when performing a more complex task. Prior research suggests that auditors rely on intelligent decision aids (e.g., Hampton & Stratopoulos, 2005). However, Commerford et al. (2021) find that auditors experience algorithm aversion when performing a highly subjective complex task. Under what circumstances are auditors more likely to make appropriate judgments in these situations?

RQ8. Prior research (e.g., Diaz & Loraas, 2010; Payne & Curtis, 2017; Salijeni et al., 2021) finds that sufficient training related to advanced technology increases the likelihood of intended use. This study also identified that perception of ease of use, confidence in memory recall, and task-specific experience influence the intended use of technology. Future research could further examine training and processing interventions that can be employed to effectively mitigate cognitive limitations such as information overload when auditors are exposed to Big Data incorporated with data analytics (see also Brown-Liburd et al., 2015).

RQ9. Prior research suggests that auditor skepticism and the precision of data analytic tools influence the level of reliance auditors place on that technology (e.g., Barr-Pulliam, Brazel, et al., 2021). We note that it is unclear whether auditors can or have developed a data analytic mindset, which will likely influence their professional skepticism and decision-making. Future research could examine methodologies that can help auditors organize and appropriately apply the information generated from data analytics to minimize judgment errors. In addition, future research could examine whether auditors can be trained to develop a data analytic mindset.

RQ10. A large body of research exists related to judgment biases and heuristics (see relevant literature discussed in Brown-Liburd et al., 2015). How does data analytics impact previously identified judgment biases experienced by auditors, and how can these biases be mitigated in a data analytic environment? See also Ruhnke (2021).

RQ11. Emett et al. (2021) find that external reviewers perceive auditor effort as lower when using advanced data analytics. Future research could extend this study by examining whether and how the use of advanced technology in the audit, particularly predictive and prescriptive analytics, impacts auditors' trait and state skepticism.

8.3 | Task-specific factors

RQ12. Audit firms invest in more advanced data analytic tools, such as augmented and autonomous AI (see Burns & Igou, 2019). How will these tools impact the nature, extent, and timing of the audit process? When using these more advanced technologies, where does the auditor's responsibility begin and end (e.g., responsibility gap)?

RQ13. Christ et al. (2021) indicate their examination of inventory audits using drones is limited and suggests research examining other settings. Using an experimental approach allowing manipulation of variables of interest (e.g., sample size, statistical analyses), would the findings be consistent with Christ et al. (2021)?

RQ14. Scant research examines prescriptive analytics. As with other types of analytic tools (e.g., CA, population testing), research examining task-specific aspects of, or ways that practitioners and researchers can apply existing tools (e.g., AI) to anticipate “what should be done” represents a valuable exercise.

9 | CONCLUSIONS AND IMPLICATIONS FOR PRACTICE, FUTURE RESEARCH AND STANDARD-SETTING

9.1 | Practice implications

While the proliferation of firm-developed and other technology has developed rapidly, auditors' adoption of that technology lags, despite the noted benefits of technology. The digital transformation journey differs by firm characteristics (e.g., size), client characteristics, and individual auditor characteristics (e.g., algorithm aversion, firm tenure).

We reviewed the literature published in the past 20 years and emerging research to understand the pace of digital transformation in the external audit setting. We categorized this study according to its focus on person-specific, task-specific, or environmental factors and the complexity of the underlying analytic technology (i.e., descriptive, diagnostic, predictive, prescriptive). Significant opportunities exist to improve our understanding of how auditors' use of these technologies influences judgment, decision-making, and audit quality.

The literature focuses heavily on, and practice currently reflects, the relatively less complex descriptive and diagnostic analytics. CA and CM have been used for over 25 years (e.g., Vasarhelyi & Halper, 2018); however, the level of automation enabled by these types of analytic tools provides a platform for future developments. While firm's leveraging the added value of the more advanced analytics (e.g., predictive and prescriptive analytics) is tempting, continuing the digital transformation in the usual systematic and rational manner that auditors apply to the audit process is prudent.

9.2 | Research implications

We provide several avenues for future research informed by our joint judgment and decision-making (e.g., Bonner, 2008) and data analytic complexity framework. The pathways for researchers suggest a shift toward studies of behavioral implications of auditors' use of advanced analytics in concert with firms' digital transformation journey. Rather than focusing on the technology's technical aspects (e.g., task-specific factors), we suggest more theory-driven experimental and quantitative (e.g., survey) studies. This approach could increase the publication likelihood in top-tier, general interest business journals. This suggestion neither minimizes the importance of publication in specialized journals nor the need to continue doing so. These publications form the basis of our understanding of digital transformation.

9.3 | Standard setting implications

We also offer suggestions for standards setters and regulators. Auditors consistently note a lack of technology-specific audit standards as a barrier to digital transformation. As our review suggests, auditors, and their firms are influenced by regulators' perceptions of their work (e.g., Austin et al., 2021; Salijeni et al., 2021). As previously noted, despite the promise of drone technology improving audit quality related to physical observation and inspection of assets at the substantive phase of the audit (Appelbaum & Nehmer, 2017), interviews with national-level audit partners and standards setters reveal that firms have concerns about being the first movers and a general lack of guidance from standards setters (Christ et al., 2021). Regulators could consider providing specific guidance on emerging technologies in the audit. For example, in the case of AI, regulations may guide auditors on (i) *using client data to develop auditing algorithms*; (ii) *auditor reliance on complex, opaque algorithms;* and (iii) the *level to which algorithms can perform judgment tasks autonomously* during the audit (Munoko et al., 2020). Further, specific guidance will potentially mitigate auditor perception of technological innovation as an addition to traditional audit procedures rather than an enhancement. This type of perception results in over auditing because auditors will continue to run the traditional and technology-enhanced procedures in parallel. Collaborations between academia, audit firms, standards setters and regulators can yield significant insight into adopting emerging technologies in auditing (i.e., Zhang et al., 2012).

Similarly, Dai and Vasarhelyi (2017) call for blockchain research and regulation advancements to identify the benefits to the assurance practice from this emerging technology. The recommendations encourage standards setters and regulators to provide guidance on preventing inappropriate activities on Blockchain and update standards to capture auditors' responsibilities when Blockchain is used as an accounting system by the client (e.g., new audit assertions arising with Blockchain). Salijeni et al. (2021) also describe how data analytics require auditors to coordinate with other functions within the firm, like data specialists. Existing auditing standards related to the use of specialists in the engagement should be evaluated to ensure they apply in this setting.

Lastly, while the IAASB's standard-setting strategy includes future-proofing its standards, we recommend that the Board considers the challenges, speed of implementation, and consequences of revised auditing standards. That is, compliance with standards disproportionately impacts smaller firms. However, evaluating whether this disparity necessitates a tiered approach to audit standards is a valuable exercise. Researchers could help standards setters to evaluate whether this leads to two tiers of (perceived) audit quality. Our literature survey is a first step in understanding the answers (or lack thereof) to these pressing questions.

ACKNOWLEDGEMENTS

We appreciate helpful comments from the editors, Donna Street and Elizabeth Gordon; Amanda Carlson, and Roger Simnett. We also appreciate research assistance from Idunnu Idunnuoluwa.

ENDNOTES

[1] While we recognize that accounting firms, and professional accounting bodies (IAASB, AICPA, etc.) have written about the impact of the digital transformation on the audit process, our literature review focuses on more theoretical academic research. Further, the professional literature does not address the technnology-auditor interation emphasis, which is the main focus of our literature review. The Big 4 accounting firms, for example, issue audit quality reports each year that, in part, discussion technology and innovating the audit. See the most recent reports for Ernst & Young (here), Deloitte (here), KPMG (here), and PwC (here).

[2] The ABDC list is available at: https://abdc.edu.au/research/abdc-journal-quality-list/

[3] See issued documents at Technology | IFAC (iaasb.org).

[4] All PCAOB Inspection reports have a public portion (Part I) that "describes audit deficiencies where inspection staff found that the auditor failed to gather sufficient audit evidence to support an audit opinion." Some reports also include a nonpublic portion that discusses firm quality controls (Part II). Part II is only released if the firm fails to remediate the identified quality control deficiencies to the PCAOB's satisfaction within 12-months of the release of the inspection report. See more on the inspection process here: https://pcaobus.org/oversight/inspections/inspection-procedures

[5] VOSviewer is a bibliometric analysis software that is used to construct networks based on co-occurrence of items such as terms or authorship. VOSviewer has been used in numerous publications (https://www.vosviewer.com/publications).

[6] Gephi is a widely used software for exploring and graphing networks (Bastian et al., 2009).

[7] The authors partnered with the AICPA's Assurance Research Advisory Group (ARAG) to recruit participants. This grant gives research access to regional and national firms outside the largest eight, that volunteered to assist ARAG in facilitating research.

8 Participants were received through a grant from the AICPA ARAG (see endnote 4).

9 Amazon's Mechanical Turk (MTurk) a crowdsourcing website that academics across disciplines use to identify research participants to complete discrete on-demand tasks. Use of MTurk for auditor litigation research is common (see, e.g., Farrell et al., 2017).

10 We did not identify any studies examining presecriptive analytics in the category related to task-specific factors.

11 There are two other types of AI systems. Assisted AI supports decision making and performs routine repetitive tasks. Autonomous AI adapts to different situations and acts independently (Munoko et al., 2020).

12 *An Audit of Internal Control Over Financial Reporting That Is Integrated with An Audit of Financial Statementsi (*Auditing Standard No. 5) Available at: https://pcaobus.org/Standards/Auditing/Pages/Auditing_Standard_5.aspx); *Evaluating Audit Results* (Auditing Standard No. 14). Available at: https://pcaobus.org/Rulemaking/Docket%20026/Release_2010-004_Risk_Assessment.pdf); and *Auditing Accounting Estimates* (AU Section 342). Available at: https://pcaobus.org/Standards/Auditing/Pages/AU342.aspx

13 Eulerich et al. (2021, p. 1) "the design science approach involves identifying important, practice-relevantproblems, determining criteria for measuring improvement, creating a potential solution (called an artifact) that can be used in practice, systematically testing the artifact against the criteria, improving the artifact to acceptable levels, and then communicating the results. In following this process, we also learn important insights that inform theory and suggest important avenues for future research."

14 Generally, fraud studies consist of archival research that focuses on predicting fraudulent versus non-fraudulent firms based on already issued financial reports (Albizri et al., 2019).

15 CA and CM are often used interchangeably. However, they are different methodologies. Rezaee, Sharbatoghlie, Elam and McMickle (2002) define CA as "a comprehensive electronic audit process that enables auditors to provide some degree of assurance on continuous information simultaneously with, or shortly after, the disclosure of the information." Whereas CM is defined as a subset of CA (Alles et al., 2006) and management implemented automated process to determine on a recurring and repetitive basis if activities follow established policies and procedures (Daigle et al., 2008).

16 While this study was done in 2004, there is increasing discussion of CA/CM by audit firms and practice-oriented publications (e.g., Journal of Accountancy).

17 CM and CA are not new methodologies. Vasarhelyi and Halper (2018) introduced the methodologies in their study of the implementation of a monitoring and control process used on billing data at a large international telecommunications company. Since then, numerous research studies have been conducted on CM and CA. We do not reiterate those studies, but rather discuss CM/CA in the context of emerging technologies. For a review and analysis of this literature see Rezaee et al. (2002).

18 Gomaa et al. (2019) developed an instructive case on blockchain that provides an overview of the steps required to install a Digital Wallet; the importance of adding specific cryptocurrencies to the wallet; a description of how to execute a transaction; illustrative methods useful in reviewing existing transactions from multiple stakeholder perspectives; tax implications of using cryptocurrencies; and a discussion of the link between a company's enterprise risk management system and transaction-level information on the blockchain.

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How to cite this article: Barr-Pulliam, D., Brown-Liburd, H. L., & Munoko, I. (2022). The effects of person-specific, task, and environmental factors on digital transformation and innovation in auditing: A review of the literature. *Journal of International Financial Management & Accounting*, 1–38. https://doi.org/10.1111/jifm.12148