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1

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Emerging technologies maturity in external audits: insights from auditors

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Abstract

Purpose – The objective of this study is to examine audit firms' maturity in adopting emerging technologies across three dimensions: people, process and technology, and to identify the factors that shape this maturity.

Design/methodology/approach – Using a structured maturity assessment framework, the study adopted a quantitative approach, employing descriptive statistics, MANCOVA, MANOVA and univariate regressions on data from 166 experienced auditors.

Findings – Findings reveal that audit firms are currently at a moderate level of maturity. However, Big Four firms are transitioning from moderate to advanced stages, while non-Big Four firms are progressing from early to moderate stages. Organizational support and the use of emerging technologies for complex audit evidence collection are associated with higher maturity levels. Furthermore, frequent use of emerging technologies for audit evidence collection and auditor satisfaction are positively correlated with maturity.

Research limitations/implications – The study uses auditors' perceptions of adoption, as captured through a survey, which may differ from actual adoption due to social desirability bias.

Practical implications – The moderate level of emerging technology adoption, with non-Big Four firms below this level and Big Four firms transitioning toward the advanced stage, offers a nuanced understanding of the persistent adoption gap. The findings also emphasize the importance of formal, firm-wide policies and guidelines tailored to appropriate technologies that enhance adoption maturity and auditor satisfaction. Furthermore, it is crucial for audit firms to integrate and frequently use emerging technologies when performing complex procedures, such as analytical procedures and inspections, to progress toward maturity. These findings underscore the need for proactive regulatory guidance to advance technology adoption in auditing.

Originality/value – This study is the first to explore the maturity level of emerging technology adoption in external audits using a structured assessment framework.

Keywords Emerging technologies, Audit technology maturity, Auditor perceptions, External auditing

Paper type Research article

1. Introduction

In the contemporary audit environment, the integration of emerging technologies [1] into audit processes is said to have transformative and revolutionary effects (Austin *et al.*, 2021; Barr-Pulliam *et al.*, 2022; Salijeni *et al.*, 2019), with their touted potential to enhance the efficiency and effectiveness of the audit process (e.g. Barr-Pulliam *et al.*, 2022; Cao *et al.*, 2015; Christ *et al.*, 2021). Audit firms are investing billions of dollars in these technologies, especially the Big Four audit firms (Deloitte, 2022; EY, 2018; KPMG, 2019; PwC, 2019). Despite the proclaimed benefits, contemporary empirical evidence suggests that audit firms have been slow to adopt emerging technologies (Austin *et al.*, 2021; Eilifsen *et al.*, 2020; Gepp *et al.*, 2018; Salijeni *et al.*, 2019), while others have identified factors contributing to resistance to adopting these technologies (e.g. Schmidt *et al.*, 2020; Fotoh and Mugwira, 2024). While

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contemporary studies (e.g. Barr-Pulliam *et al.*, 2022) highlight disparities in emerging technology adoption within audit firms, there is limited research examining audit firms' maturity in adopting these technologies and the factors influencing this maturity—even though such understanding is crucial and should precede investigations into slow adoption and resistance. Therefore, the objective of this study is to examine audit firms' maturity in adopting emerging technologies across three dimensions: people, process, and technology, and to identify the factors that shape this maturity.

The audit profession has historically been rooted in manual processes that rely on physical audit procedures (e.g. inspections and observations) to gather audit evidence. The advent of emerging technologies such as artificial intelligence, machine learning, blockchain, and data analytics is revolutionizing the audit process (Appelbaum *et al.*, 2017; Appelbaum and Nehmer, 2017; Austin *et al.*, 2021; Barr-Pulliam *et al.*, 2022; Cao *et al.*, 2015; Christ *et al.*, 2021; Kokina and Davenport, 2017). These technologies provide auditors with unprecedented capabilities, including enhancing efficiency and effectiveness (Christ *et al.*, 2021), analyzing vast datasets (Brown-Liburd and Vasarhelyi, 2015; Earley, 2015; Yoon *et al.*, 2015), and deriving meaningful insights (Sun and Vasarhelyi, 2018), thereby transcending the limitations of traditional audit methodologies. However, successfully integrating emerging technologies into external audit processes necessitates a nuanced understanding of their maturity levels.

Despite the global strategies to promote the integration of emerging technologies into audit and their widely acknowledged benefits in enhancing audit efficiency, effectiveness, and audit quality, empirical evidence consistently shows that audit firms have been slow to adopt these technologies (Austin *et al.*, 2021; Eilifsen *et al.*, 2020; Gepp *et al.*, 2018; Salijeni *et al.*, 2019). While some studies have examined barriers to adoption, such as resistance, a lack of digital competencies, and insufficient regulation (Austin *et al.*, 2021; Fotoh and Mugwira, 2024; Schmidt *et al.*, 2020), a critical gap persists in understanding the maturity of technology use within audit firms. Assessing maturity is vital because it transcends binary adoption metrics to reveal how deeply and effectively technologies are embedded into audit processes. Such knowledge is crucial in understanding the slow adoption and resistance to adopting emerging technologies. A nuanced understanding of maturity levels is therefore essential to identify where firms stand on the digital adoption and transformation spectrum, and what factors influence their progress. Accordingly, maturity assessment is not only timely but also central to advancing both scholarly inquiry and professional practice in the audit field.

Prior research suggests that successful technology adoption depends on three factors: technology, process, and people (Coderre, 2015). In other words, adoption depends not only on available technology but also on people and process aspects, which are interdependent. These three aspects provide a holistic view of technology maturity and prevent an overly narrow focus on just one or two dimensions. For example, organizations may invest in technology yet fail to realize its benefits because of skills gaps or inefficient processes, resulting in low maturity levels. This study empirically assesses the maturity of emerging technology use and the factors contributing to it in external audits using a maturity assessment framework. To the best of our knowledge, it is the first to apply such a framework to evaluate both the maturity of emerging technology and the factors shaping it in external audits.

This study adopts a maturity assessment framework based on Smidt's (2016) framework, which was originally developed to assess the maturity of Generalized Audit Software (GAS) use in internal auditing within the banking sector (Smidt, 2016; Van der Nest *et al.*, 2017). It has since been applied in a range of contexts, including the internal audit function in the private sector in Taiwan (Wu and Huang, 2025), the federal government of Canada (Steenkamp *et al.*, 2023), and the Institute of Internal Auditors Australia (Smidt *et al.*, 2019). Given the differences between internal and external auditing, we adapted the framework for use in the external audit context. The framework evaluates three critical dimensions for successful technology integration: people, process, and technology (Coderre, 2015). Unlike technology adoption theories, the people–process–technology maturity assessment framework is specifically designed to assess technology maturity within the broader auditing context, rather than merely capturing users' perceptions of internal and external factors influencing technology adoption. It examines how effectively technology is integrated, optimized, and aligned with organizational processes to determine overall maturity.

Our study makes several contributions to both literature and practice. First, it extends prior research (Austin *et al.*, 2021; Eilifsen *et al.*, 2020; Fotoh and Mugwira, 2024; Gepp *et al.*, 2018; Salijeni *et al.*, 2019; Schmidt *et al.*, 2020), which has documented the slow adoption and resistance to emerging technologies in auditing, by examining audit firms' maturity in adopting these technologies and identifying the factors/drivers that shape this maturity. By showing that audit firms are generally at a moderate level of adoption (with non-Big Four firms below this level and Big Four firms transitioning toward the advanced stage), this study offers a nuanced understanding of the persistent adoption gap. It provides empirical depth to existing findings by demonstrating that slow adoption and resistance are primarily driven by where audit firms currently stand along the maturity framework.

Second, this study employs a comprehensive maturity assessment framework that transcends a sole focus on technology by incorporating three critical dimensions: technology, people, and process, offering a well-rounded benchmark for future research on the maturity of emerging technologies in external auditing. These dimensions must develop in tandem for audit firms to achieve advanced maturity in technology adoption and to realize the touted benefits in terms of audit efficiency, effectiveness, and audit quality. The framework enhances understanding of how audit firms progress toward full adoption of emerging technologies.

Third, the study contributes to both theory and practice by underscoring the importance of organizational support, employing emerging technologies in complex audit evidence-gathering tasks, exposure to these technologies for audit evidence collection, and enhanced auditor satisfaction and experience, associated with higher levels of technological maturity. From a practical perspective, the study offers a benchmark that audit firms can use to evaluate their own maturity levels within the profession. The findings also provide audit regulators and standard setters with a broader understanding of audit firms' technological maturity, informing policymaking, such as the potential integration of technology maturity frameworks into audit inspection processes or guidance materials. Moreover, the observed differences in maturity between Big Four and non-Big Four firms suggest a need for differentiated regulatory oversight. Collectively, this study offers a timely perspective on technology adoption in the post-COVID-19 audit environment, where the pandemic has been widely touted as a catalyst for the accelerated use of technologies in remote auditing (Altiero *et al.*, 2024; Lorentzon *et al.*, 2024). At the same time, recent studies show that some audit activities continued to rely on basic technologies such as cloud-based platforms and remote communication tools (Altiero *et al.*, 2024; Fotoh *et al.*, 2025), while others preferred traditional manual procedures over technological solutions (Fotoh, 2025).

2. Literature review, conceptual perspective and hypothesis development

2.1 Literature review of emerging technologies

In the auditing context, emerging technologies refer to several technologies, including but not limited to big data analytics (BDA), artificial intelligence (AI), robotic process automation (RPA), drones, and blockchain technology (IFAC, 2020), which are applied in the audit process to enhance overall audit quality. In general, emerging technologies can facilitate various audit procedures, including inspection, observation, inquiry, confirmation, recalculation, reperformance, and analytical procedures (Appelbaum and Nehmer, 2017). BDA generally involves the use of advanced analytics on big data (Cao *et al.*, 2015) to facilitate the analysis of both structured and unstructured data (Richins *et al.*, 2017). Information from BDA can provide useful audit evidence, as it is acquired from multiple sources (Yoon *et al.*, 2015). Some information from BDA can also be independent of the client, such as insights from social media and e-tracking technology (Murthy and Geerts, 2017; Yoon *et al.*, 2015). When this externally sourced information is combined with client-provided information, it increases the authenticity of audit evidence. Overall, BDA is widely recognized for its potential to enhance risk assessment, full population testing, anomaly detection, control assessment, compliance monitoring, and fraud detection (e.g. Brown-Liburd *et al*., 2015; Cao *et al*., 2015; Earley, 2015; Salijeni *et al*., 2019; Schneider *et al*., 2015).

AI has been touted for its ability to emulate human intelligence when performing tasks (Vetter, 2018). In certain audit procedures, such as interviewing, AI can enhance efficiency, effectiveness, and audit quality (Pickard *et al*., 2020). AI can also assist auditors in decision-making. For example, deep learning, a component of AI, can improve auditors' judgment and decision-making by analyzing structured and unstructured data as supplementary audit evidence through its capabilities in text understanding, speech recognition, and visual recognition (Sun, 2019). The speech and visual recognition capabilities of deep learning can enhance audit processes. For instance, deep learning's speech recognition potential can improve fraud detection during interviews by identifying deception through suspicious answers or longer pauses in responses (Sun, 2019). Similarly, its visual recognition capabilities are valuable during the verification phase, as they facilitate the examination of images and scanned documents (e.g. checks, bank statements, receipts, proofs of claim) to assess the authenticity and validity of the selected items (Sun, 2019).

Machine learning (ML), another component of AI, is defined as a discipline that enables computers to learn autonomously (Koza *et al*., 1996). In auditing contexts, ML refers to the ability of computer algorithms to identify patterns and trends in historical datasets with minimal human assistance, enabling entities to perform predictive analyses and make more informed decisions (Bakarich and O'Brien, 2021). Prior studies (e.g. Bao *et al*., 2020) document the successful use of ML in predicting irregularities and fraud, identifying anomalies in large data sets (Kokina and Davenport, 2017), and detecting material misstatements (Bertomeu *et al*., 2021). Consequently, ML in the audit context can lead to robust predictive analytics and better-informed decision-making.

RPA is efficient in automating repetitive, mundane, and low-judgment tasks, thereby improving operational efficiency, reducing costs, and enabling auditors to focus on more complex activities (Cooper *et al*., 2019, 2022; Moffitt *et al*., 2018). For instance, Cooper *et al*. (2019) reported that one firm saved over one million human hours by implementing RPA. Additionally, RPA demonstrated greater accuracy than humans when performing the same tasks (Cooper *et al*., 2019). However, RPA cannot make complex decisions, limiting its applicability in the audit process (Zhang, 2019). Another factor limiting RPA implementation in audits is the lack of clear frameworks and RPA expertise, as this knowledge is often concentrated within specific individuals and teams, with no clear channels for disseminating it to others (Eulerich *et al*., 2022).

Blockchain can enhance audit evidence collection and enable continuous auditing through real-time verification, reconciliation, and approval, thereby enhancing data reliability through automated controls (Liu *et al*., 2019; Schmitz and Leoni, 2019; Kokina *et al*., 2017). Blockchain further enhances audit efficiency by reducing the risk of human errors, decreasing the time spent reconciling records with clients, simplifying audits by facilitating fraud investigation, and improving auditors' understanding of a client's business (Schmitz and Leoni, 2019). Furthermore, blockchain technology has been trumpeted for its secure electronic system in smart contracts (Dai and Vasarhelyi, 2017). Smart contracts are programs that automatically execute specific transactions when activation conditions are met (Al-Saqaf and Seidler, 2017). Incorporating blockchain in auditing can enable a smart-based assurance approach, where smart controls are embedded into smart contracts (Fanning and Centers, 2016). Additionally, all accounting documents can be stored on the blockchain, enhancing the audit trail and facilitating remote auditing, as auditors can access this information remotely within the chain (Dai and Vasarhelyi, 2017). Blockchain can also reduce misstatements and fraudulent manipulations since information in the chain must be approved by multiple parties (Liu *et al*., 2019). This may result in accurate, cost-effective, real-time audits of financial statements (Dai and Vasarhelyi, 2017; Schmitz and Leoni, 2019).

Drones can enhance the collection of audit evidence. Specifically, they can facilitate inspection, observation, evaluation, and the performance of particular audit procedures, reducing the chances of human error (Appelbaum and Nehmer, 2017; Christ *et al.*, 2021). Therefore, drones provide evidence related to valuation and specific audit assertions in particular scenarios (Appelbaum and Nehmer, 2017). Drones are particularly crucial for inventory audit processes, where they can improve overall efficiency and effectiveness, enhance the quality of documentation, and strengthen audit quality (Christ *et al.*, 2021).

2.2 The maturity assessment framework

This study adopts a maturity assessment framework based on Smidt's (2016) framework, originally developed to assess the maturity of Generalized Audit Software (GAS) use in internal auditing within the banking sector (Smidt, 2016; Van der Nest *et al.*, 2017). The framework has since been applied in other internal audit studies (Smidt *et al.*, 2019; Steenkamp *et al.*, 2023; Van der Nest *et al.*, 2017; Wu and Huang, 2025). Because the original maturity-level assessment framework was developed for internal auditing, modifications were made to adapt it for external audit environments [2]. This framework assesses technology maturity across six levels. The first two levels (non-existent and ad hoc) represent the most basic or introductory stages, where emerging technologies are rarely used and seldom applied in high-level risk assessment audits. The next two levels (developing and repeatable) indicate moderate maturity. At this stage, descriptive and diagnostic analytics are used in their initial or repeatable stages. Specialists and technology teams may be involved in the audit process as firms begin adopting specific tools, such as data visualization software and basic built-in functions of emerging technologies. The final two levels (embedded and monitoring) reflect the highest level of maturity on the continuum, where maturity is fully established. At this stage, external audit functions involve specialists and rely on advanced emerging technologies with predictive capabilities.

These six levels of maturity were assessed based on three key aspects of technology adoption: people, process, and technology (Coderre, 2015). The people aspect refers to the human capital available to work with emerging technologies (Plachkinova and Knapp, 2023), including audit staff, audit managers, audit partners, and technology specialists who assist in audit work. Audit firms must identify the appropriate level of technological skills and capabilities required to effectively use emerging technologies in the audit process. The people aspect can be enhanced by hiring emerging technology specialists to assist auditors or by providing training opportunities to equip auditors with the knowledge and competencies needed to use emerging technologies effectively in the audit process. Additionally, audit firms should foster a culture that embraces change rather than resisting the adoption of emerging technologies.

The process aspect refers to the use and integration of emerging technologies throughout all phases of the audit engagement, from planning to reporting. This aspect addresses attributes such as interdependence and complexity in the various tasks and procedures performed during the audit engagement, and how these attributes influence the adoption of emerging technologies. The technology aspect relates to the specific emerging technologies that auditors can use in external audit engagements, including their suitability, usability, functionality, and effectiveness in performing audit procedures throughout the audit process. This includes matching different categories of technology to specific audit tasks and processes. For successful technology adoption, these three aspects must be managed efficiently to ensure a proper fit among them. In other words, they must work in harmony to facilitate the adoption of emerging technologies. Audit firms must foster synergy among these aspects so that each reinforces the other. If any aspect is poorly managed, adoption will be inefficient. The three aspects are interdependent, and changes in one may impact the other. Therefore, our study presents an overall maturity assessment based on a combined evaluation of these three individual aspects.

To further justify the use of the PPT maturity framework in this study, we explicitly differentiate it from traditional technology-adoption models. Technology maturity is not solely determined by whether a technology has been adopted; rather, it reflects the extent to which it is effectively integrated, optimized, and aligned with human and procedural elements within the organization. The PPT framework offers a holistic approach for evaluating organizational maturity because it considers the interaction among people, processes, and technology, which collectively constitute the foundation of operational capability (Smidt, 2016; Smidt *et al.*, 2019; Steenkamp *et al.*, 2023; Van der Nest *et al.*, 2017). In contrast, traditional technology-acceptance theories, such as the Technology-Organization-Environment (TOE) framework (Tornatzky *et al.*, 1990), the Technology Acceptance Model (TAM) (Davis, 1985; Venkatesh and Davis, 2000), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003), adopt a narrower focus. These theories emphasize internal and external contextual factors within the environment and organization (Tornatzky *et al.*, 1990) and user perceptions, including perceived usefulness and ease of use (Davis, 1985; Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003). While these factors are critical for understanding initial adoption decisions, they are insufficient for evaluating long-term technology integration, optimization, and maturity.

Thus, acceptance-based frameworks such as TOE, TAM, and UTAUT primarily explain why organizations may adopt a technology (Davis, 1985; Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003) rather than how well that technology matures over time and becomes integrated into audit processes. The PPT framework, however, enables continuous maturity assessment by examining whether individuals are appropriately trained, whether processes in audit firms are standardized and continuously improved, and whether technology is effectively utilized to achieve strategic objectives (Smidt, 2016; Smidt *et al.*, 2019; Steenkamp *et al.*, 2023; Van der Nest *et al.*, 2017). Accordingly, PPT is well-suited for assessing technology maturity because it evaluates integration and operational optimization within a broader organizational context, rather than focusing solely on adoption drivers.

2.3 Hypotheses development

From the status quo bias perspective, Kim and Kankanhalli (2009) argue that organizational support through actions, resources, and policies is crucial for the successful adoption of new technologies within organizations. This generally entails creating a supportive environment that embraces and facilitates using emerging technologies (Kim and Kankanhalli, 2009). Prior research uncovered that organizational support not only narrows resistance to change (Schmidt *et al.*, 2020) but also facilitates switching to emerging technologies to enhance client data analysis (Fotoh and Mugwira, 2024). Furthermore, organizational training on emerging technologies reinforces the importance of technological skills and competence development to facilitate the adoption of emerging technologies (Igou *et al.*, 2023; Vitali and Giuliani, 2024). Integrating these insights, we propose that increased organizational engagement with emerging technologies, through supportive actions, resource allocation, formal policies, and applied use in data analysis, can lead to a higher maturity assessment of these technologies within audit firms. Therefore, we hypothesize:

H1. Enhanced organizational engagement towards emerging technologies is positively associated with a high maturity assessment rating.

Audit evidence is the cornerstone of the audit process and underpins the audit opinion, which is typically derived from the evidence collected during audit procedures (Wright and Mock, 1985). Current standards require that auditors obtain sufficient appropriate audit evidence to support audit opinions (SAS No. 106, para. 2, AICPA, 2006; AS No. 15, para. 2, PCAOB, 2010a; ISA 500, para 5, IFAC, 2008a), which is essential for conducting efficient audits (Wright and Mock, 1985). The methods for obtaining audit evidence generally include a mix of observation, inquiry, confirmation, recalculation, reperformance, analytical procedures, and inspection of documents, records, and tangible assets (SAS No. 106, para. 20–42, AICPA, 2006; ISA 500, A2, IFAC, 2008b). These methods can be categorized by complexity, ranging from relatively simple techniques (such as observations, confirmations, and inquiries) to more complex procedures (such as analytical procedures and inspections). Contemporary research (e.g. Appelbaum and Nehmer, 2017; Appelbaum *et al.*, 2020; Christ *et al.*, 2021; Eilifsen *et al.*, 2020) highlights how emerging technologies enhance several of these audit evidence-gathering procedures. Specifically, emerging technologies can efficiently and effectively perform time-consuming, complex audit evidence-gathering tasks, potentially resulting in time savings and enabling auditors to focus on more judgment-intensive tasks (Barr-Pulliam *et al.*, 2022, 2024; Christ *et al.*, 2021). Given this, the nature and complexity of audit evidence collection methods may be associated with the level of maturity assessment, where the use of emerging technologies in complex audit evidence procedures may correspond to a higher maturity assessment rating. Based on this, we hypothesize:

H2. The use of emerging technologies in complex audit evidence collection procedures is positively associated with a higher maturity assessment rating.

The frequency of technology use and exposure to its features significantly impact acceptance and usage rates (Davis *et al.*, 1989; Kim *et al.*, 2009). Similarly, Rogers (2003) emphasizes that the extent to which a technology is trialed or experimented with influences its adoption. Along the same lines, Fotoh and Mugwira (2024) argue that frequent use of and exposure to emerging technologies narrows resistance to change and facilitates the switch to emerging technologies. Their findings suggest that the more users experience the benefits of emerging technologies, the more likely they are to adopt them. In the auditing context, frequency of use may involve employing these technologies specifically for audit evidence collection or more broadly across the entire audit process. Taken together, this discussion suggests that the extent and proportion of emerging technology use by auditors are likely to impact their maturity assessment of these technologies. Consequently, we hypothesize:

H3. Increased use, exposure, and frequency of emerging technologies in the overall audit process are positively associated with a high maturity assessment rating.

Satisfaction is a subjective judgment that technology provides significant fulfillment relative to the desired need or goal (Deng *et al.*, 2010). It reflects the cumulative feelings developed over multiple interactions with a service provider (Oliver, 1980). Research indicates that satisfaction strongly influences continuance intention and behavior (Deng *et al.*, 2010; Kuo *et al.*, 2009; Liu *et al.*, 2011), potentially affecting maturity ratings. According to Ajzen and Fishbein's (1980) theory of reasoned action, satisfaction denotes a positive attitude, leading to increased positive behavioral intentions or actions. Thus, if auditors are satisfied with emerging technologies, they are likely to rate maturity highly.

H4. Greater satisfaction with emerging technologies is positively associated with a high maturity assessment of these technologies.

We incorporate auditors' experience with emerging technologies and firm size as control variables to explain potential differences in maturity assessment ratings in all four hypotheses. Auditors with prior experience using emerging technologies are more likely to rate them favorably than those without such experience. This assumption is based on the rationale that experienced auditors have likely observed the efficiency and effectiveness gains highlighted in current research (e.g. Barr-Pulliam *et al.*, 2022; Cao *et al.*, 2015; Christ *et al.*, 2021). Similarly, firm size is a relevant factor, as Big Four firms, given their complex client portfolios and greater resource availability, are more likely to invest in and adopt emerging technologies. In contrast, non-Big Four firms, which typically serve less complex clients and operate with fewer resources, tend to adopt these technologies more slowly (Janvrin *et al.*, 2008, 2009; Lawrence *et al.*, 2011). Consequently, Big Four firms are more likely to perceive and rate these technologies as important compared to non-Big Four firms (Janvrin *et al.*, 2008; Lowe *et al.*, 2018), potentially resulting in differences in maturity assessment ratings.

3. Methodology

3.1 Research instrument

To assess the maturity level of emerging technology adoption, we conducted a survey [3] among auditors in Sweden. Given that surveys are commonly used to gather data on perceptions (e.g. Ferri *et al.*, 2021), this method is appropriate for empirically examining auditors' perceptions of their maturity in adopting emerging technologies. The survey began with demographic questions, followed by a tailored maturity assessment framework adapted from internal audit studies to evaluate emerging technology adoption in external audits across technology, people, and process dimensions. Participants selected one of six maturity levels that best described their audit firm's current stage for each dimension. Following these assessments, respondents answered additional Likert-scale items regarding how their firms adopt emerging technologies in external audit engagements.

To enhance content validity, we adopted survey items from existing literature and standards. The three maturity assessment measures (people, process, and technology) were obtained from Coderre (2015). Four items measuring organizational support were adapted from prior studies (Kim and Kankanhalli, 2009; Fotoh and Mugwira, 2024; Igou *et al.*, 2023; Vitali and Giuliani, 2024). Five items related to audit evidence collection procedures were derived from current auditing standards (SAS No. 106, para. 20–42, AICPA, 2006; ISA 500, A2, IFAC, 2008b). Two items measuring exposure to and frequency of emerging technology use were adapted from the literature (Davis *et al.*, 1989; Fotoh and Mugwira, 2024; Kim *et al.*, 2009). Finally, the item assessing satisfaction was drawn from the literature (Ajzen and Fishbein, 1980; Deng *et al.*, 2010; Kuo *et al.*, 2009; Liu *et al.*, 2011; Oliver, 1980). A five-point Likert scale was used, consistent with recent studies on perceptions (e.g. Bailey *et al.*, 2024; Barnes *et al.*, 2024; Fotoh, 2025).

3.2 Data collection and participants

The survey was administered via SUNET [4] between March and August 2023 to 1,365 auditors randomly selected from the Swedish register of auditors. We received 166 usable responses, corresponding to a 12.2% response rate [5], with respondents representing both Big Four (39.2%) and non-Big Four (60.8%) audit firms. A majority of participants were highly experienced, with 65% reporting more than 15 years of audit experience, and 40.4% indicating over 5 years of experience using emerging technologies in audit engagements [6]. Of the respondents, 69.3% identified as male and 30.7% as female. Table 1 presents the demographic information of participants. Regarding the use of emerging technologies in their audit firms (where participants could select multiple options), 59.6% reported using advanced data analytics, 33.1% reported using RPA, and 45.2% indicated using cloud computing. A smaller proportion reported using blockchain (4.8%) and drone technology (6%) in their audit engagements (See Table 2) [7].

Given the potential for bias due to the voluntary nature of surveys, we addressed this concern by assessing nonresponse bias. Following Armstrong and Overton (1977), we treated early respondents as a proxy for the standard respondents and late respondents as a proxy for nonrespondents. Independent sample t-tests revealed no significant differences between early and late respondents in terms of age ($t = -1.062$, $p = 0.290$), audit experience ($t = -0.655$, $p = 0.514$), and experience with emerging technologies ($t = -0.965$, $p = 0.337$), suggesting no evidence of nonresponse bias. To reduce the risk of common method bias (CMB), we implemented *ex ante* procedural remedies. These included careful survey design and clear instructions to ensure instrument clarity, a cover memo explaining the survey's purpose, and the separation of measurements for dependent and independent variables. We also grouped

Table 1. Demographic statistics

Variable	Categories	Frequency	Percentage	Cumulative percentage
Audit firm	Big four	65	39.2	39.2
	Non-big four	101	60.8	100
	Total	*166*	*100*	
Audit experience	Below 5 years' experience	3	1.8	1.8
	5–10 years' experience	31	18.7	20.5
	11–15 years' experience	24	14.5	35
	16–20 years' experience	15	9.0	44
	21–25 years' experience	39	23.5	67.5
	More than 25 years' experience	54	32.5	100
	Total	*166*	*100*	
Experience using emerging technologies	Below 1 years' experience	34	20.5	20.5
	1–2 years' experience	14	8.4	28.9
	2–3 years' experience	18	10.8	39.7
	3–5 years' experience	33	19.9	59.6
	More than 5 years' experience	67	40.4	100

Table 2. Types of emerging technologies currently used by audit firms

Type of technology	Frequency	Percentage
Advanced data analytics (ADAs)	99	59.6
Big data	44	26.5
Artificial intelligence (AI)	39	23.5
Robotic process automation (RPA)	55	33.1
Blockchain	8	4.8
Drone technology	10	6.0
Advanced streaming technology (excluding zoom, teams, etc)	43	25.9
Cloud computing	75	45.2
None (my audit firm does not use emerging technologies)	32	19.3

items measuring the same construct into distinct sections, ensured respondent anonymity to minimize socially desirable responses, and varied the order of items relative to the structure of the hypothetical model (Podsakoff *et al*., 2003; Podsakoff *et al*., 2012). Next, we conducted Harman's one-factor test as a post hoc check for CMB. The first factor accounted for approximately 50% of the total variance, which does not exceed the commonly accepted threshold (see Howard *et al*., 2024). The results suggest that common method variance is unlikely to be a major concern.

We analyzed the data using descriptive statistics (mean scores, standard deviations, and percentages) to obtain an overall understanding of the results. To test whether mean scores significantly differed from the midpoint of the Likert scale and to compare differences between Big Four and non-Big Four auditors, we conducted one-sample and independent samples *t*-tests, respectively. Given the exploratory nature of the study, we analyzed the hypotheses using multivariate analysis of covariance (MANCOVA), controlling for firm size and auditors' experience with emerging technologies. To ensure the robustness of the multivariate results, several diagnostic checks were conducted. Box's M test indicated that the assumption of homogeneity of covariance matrices was met. Levene's test confirmed equality of error variances for all dependent variables. Additionally, the interaction term between the covariate and each group independent variable was non-significant, satisfying the assumption of homogeneity of regression slopes. These results support the validity of the MANCOVA findings. The diagnostic check results are presented in Appendix. To assess the consistency of the results, we also conducted a multivariate analysis of variance (MANOVA) without the control variables. Finally, we performed follow-up univariate regression analyses to examine the effects of each independent variable specified in the hypotheses on the three dependent variables.

4. Results

4.1 Descriptive statistics

Table 3 shows that none of the three dimensions (technology, people, and process) differ significantly from the midpoint (3.5 on a 6-point Likert scale), indicating a moderate level of maturity in adopting emerging technologies. This suggests firms are neither in the early adoption stage (non-existent/ad hoc) nor in advanced stages (embedded/monitoring), but rather in the developing or repeatable phase. Table 4 corroborates these findings, with most respondents placing their firms in the developing/repeatable stage: technology (51.8%), people (54.8%), and process (53%). Fewer reported early adoption: technology (24.1%), people (23.4%), process (28.4%), or advanced maturity: technology (24.1%), people (21.7%), process (18.7%). Overall, the majority of auditors indicated their firms are in either early or moderate stages: technology (75.9%), people (78.2%), and process (81.4%), reinforcing the conclusion that maturity is generally moderate.

Table 5 shows that Big Four firms report consistently higher maturity scores than non-Big Four firms across all dimensions: technology (4.42 vs 2.81), people (4.22 vs 2.86), and process (4.15 vs 2.75). All scores differ significantly from the midpoint (3.5), indicating a clear gap in maturity levels. Big Four firms appear to be in the advanced repeatable and transitioning to embedded, while non-Big Four firms remain below moderate maturity, suggesting they are in the ad hoc stage and transitioning to developing. These results highlight a significant disparity in the adoption maturity of emerging technologies between the two groups.

Table 6 shows that both Big Four and non-Big Four auditors expressed neutrality regarding whether the implementation of such technologies was an informal arrangement left to the discretion of engagement partners or audit teams (2.95), supported by firm-level guidelines and procedures (3.11), accompanied by staff guidance on proper adoption (3.10), used for analyzing more client data compared to traditional methods (3.01), applied in fraud detection (2.93), or employed in obtaining audit evidence (2.94). Auditors somewhat disagreed that emerging technologies were used for inspection (2.78), observation (2.22), confirmation (2.70), recalculation, and reperformance (2.69), and agreed that they were used in only a limited proportion of the overall audit process (2.42). Conversely, auditors somewhat agreed that most data analytics was conducted in Microsoft Excel (3.46) and that emerging technologies were applied in analytical procedures (3.58). Overall, they reported being somewhat satisfied with their firm's use of emerging technologies (3.37).

Table 3. Perception of maturity assessment

Item	Mean (Midpoint 3.5)	SD (Standard deviation)
What maturity category with respect to TECHNOLOGY does your organization best fit into	3.44	1.420
What maturity category with respect to PEOPLE does your organization best fit into	3.39	1.352
What maturity category with respect to PROCESS does your organization best fit into	3.30	1.355

Table 4. Descriptive statistics for the technology, people and process aspects

Aspect	Nonexistence Frequency (Percentage)	Ad hoc Frequency (Percentage)	Developing Frequency (Percentage)	Repeatable Frequency (Percentage)	Embedded Frequency (Percentage	Monitoring Frequency (Percentage)
Technology	23 *(13.9%)*	17 *(10.2%)*	40 *(24.1%)*	46 *(27.7%)*	30 *(18.1%)*	10 *(6.0%)*
People	20 *(12%)*	19 *(11.4%)*	47 *(28.3%)*	44 *(26.5%)*	28 *(16.9%)*	8 *(4.8%)*
Process	23 *(13.9%)*	24 *(14.5%)*	35 *(21.1%)*	53 *(31.9%)*	26 *(15.7%)*	5 *(3%)*

Table 5. Big four and non-big four separated on the three aspects

Item	Firm size	*N*	Mean rank
Maturity assessment			
What maturity category with respect to TECHNOLOGY does your organization best fit into	Big four	65	4.42*
	Non-big four	101	2.81*
What maturity category with respect to PEOPLE does your organization best fit into	Big four	65	4.22*
	Non-big four	101	2.86*
What maturity category with respect to PROCESS does your organization best fit into	Big four	65	4.15*
	Non-big four	101	2.75*

Table 7 reveals significant differences between Big Four and non-Big Four auditors in the adoption of emerging technologies. Big Four auditors reported a greater presence of guidelines and procedures (3.86 vs 2.63) and more staff training on their application (3.91 vs 2.58). They also reported higher usage of emerging technologies than traditional methods in client data analysis (3.49 vs 2.69), fraud detection (3.48 vs 2.58), and audit evidence gathering (3.42 vs 2.63). For analytical procedures, Big Four auditors agreed on extensive use of emerging technologies (4.12), while non-Big Four auditors were neutral (3.23). Use of emerging technologies for inspection was near neutral for Big Four (3.18) but lower for non-Big Four (2.52), with a similar pattern in recalculations and reperformance (3.12 vs 2.41). Big Four auditors reported a slightly below-neutral proportion of audit engagements using emerging technologies (2.74), compared with an even lower score for non-Big Four (2.22). Overall satisfaction with the use of emerging technologies in the audit process was higher among Big Four auditors (3.65) than among non-Big Four auditors (3.20), underscoring broader integration of and greater satisfaction with emerging technologies within Big Four firms.

4.2 Hypotheses results

4.2.1 Organizational support and maturity assessment. The MANCOVA results (Wilks' lambda) support H1, indicating that enhanced organizational support is positively associated with a higher maturity assessment of emerging technologies. Among the organizational support factors, formal guidelines and procedures (ORG 2) exhibit the strongest and most significant association with maturity assessment, suggesting that audit firms with structured policies for emerging technologies tend to demonstrate higher maturity levels across people, process, and technology. Additionally, organizational training on emerging technologies (ORG 3) is positively associated with a higher maturity assessment, reinforcing the importance of skill development in the overall maturity of emerging technology adoption. Similarly, greater reliance on emerging technologies for data analysis over traditional audit methods

Table 6. Perceptions of emerging technology use and extent of satisfaction

Item	Mean	SD (Standard deviation)
The use of emerging technologies is an informal arrangement, left to the discretion of the individual engagement partner or audit team	2.95	1.124
My audit firm has developed and implemented guidelines and procedures to facilitate the use of emerging technologies in audit engagements	3.11	1.252
My audit firm provides training that offers guidance to audit staff on the proper application of emerging technologies in audit engagements	3.10	1.324
Most data analytics in my firm are performed with the use of Microsoft Excel	3.46*	1.001
My audit firm analyses more client data using emerging technologies than using traditional audit methods	3.01	1.188
To what extent does your audit firm use emerging technologies (e.g. advanced data analytics) in detecting fraudulent activities?	2.93	1.171
To what extent does your audit firm use emerging technologies to obtain audit evidence?	2.94	1.077
My audit firm mostly use emerging technologies to perform analytical procedures	3.58*	1.449
My audit firm mostly use emerging technologies to perform inspection of records, documents, and assets	2.78*	1.303
My audit firm mostly use emerging technologies to perform observations (e.g. inventory and asset observations)	2.22*	1.265
My audit firm mostly use emerging technologies to perform confirmations (to verify account balances)	2.70*	1.346
My audit firm mostly use emerging technologies to perform recalculations and reperformance	2.69*	1.343
What proportion of external audit engagements use emerging technologies in the audit process	2.42*	1.313
Rate your level of satisfaction concerning the use of emerging technologies in your audit firm	3.37*	0.930

Note(s): **Indicates $p < 0.05$ (two-tailed)

(ORG 4) is significantly associated with a higher maturity assessment. In contrast, using emerging technologies as an informal process at the discretion of individual audit partners or teams (ORG 1) is linked to a weaker maturity assessment, suggesting that firm-wide policies drive emerging technological maturity more effectively than discretionary adoption. These findings remain significant after controlling for auditors' experience with emerging technologies and audit firm size. Notably, experience in using emerging technologies (Exp) does not significantly impact maturity assessment. In contrast, firm size plays a significant role, with Big Four audit firms exhibiting a higher maturity assessment than non-Big Four firms. Table 8 presents the MANCOVA results.

Next, we conducted a MANOVA, excluding the control variables (audit firm size and experience in using emerging technologies), to examine the association between the four organizational support variables and maturity assessment. The results remain consistent with the MANCOVA findings and are statistically significant at the 0.05 level, suggesting that organizational support variables are significantly associated with the maturity of emerging technologies. The detailed MANOVA results are presented in Table 9.

Lastly, we conducted a univariate regression analysis to examine the relationships between the four organizational support variables and each maturity assessment variable. The results consistently indicate that formal guidelines and procedures (ORG 2) and greater reliance on emerging technologies for data analysis over traditional audit methods (ORG 4) are significantly associated with higher maturity levels across all three dimensions. In contrast, organizational training on emerging technologies (ORG 3) is statistically insignificant across all three dimensions (people, process, and technology) in the univariate tests, suggesting that it

Table 7. Independent sample *t*-test results for big four and non-big four firms

Item	Firm size	N	Mean rank
The use of emerging technologies is an informal arrangement, left to the discretion of the individual engagement partner or audit team	Big four	65	2.98
	Non-big four	101	2.92
My audit firm has developed and implemented guidelines and procedures to facilitate the use of emerging technologies in audit engagements	Big Four	65	3.86*
	Non-Big Four	101	2.63*
My audit firm provides training that offers guidance to audit staff on the proper application of emerging technologies in audit engagements	Big Four	65	3.91*
	Non-Big Four	101	2.58*
Most data analytics in my firm are performed with the use of Microsoft Excel	Big Four	65	3.35
	Non-Big Four	101	3.52
My audit firm analyses more client data using emerging technologies than using traditional audit methods	Big Four	65	3.49*
	Non-Big Four	101	2.69*
To what extent does your audit firm use emerging technologies (e.g. advanced data analytics) in detecting fraudulent activities?	Big Four	65	3.48*
	Non-Big Four	101	2.58*
To what extent des your audit firm use emerging technologies to obtain audit evidence?	Big Four	65	3.42*
	Non-Big Four	101	2.63*
My audit firm mostly use emerging technologies to perform analytical procedures	Big Four	65	4.12*
	Non-Big Four	101	3.23*
My audit firm mostly use emerging technologies to perform inspection of records, documents, and assets	Big Four	65	3.18*
	Non-Big Four	101	2.52*
My audit firm mostly use emerging technologies to perform observations (e.g. inventory and asset observations)	Big Four	65	2.29
	Non-Big Four	101	2.17
My audit firm mostly use emerging technologies to perform confirmations (to verify account balances)	Big Four	65	2.88
	Non-Big Four	101	2.58
My audit firm mostly use emerging technologies to perform recalculations and reperformance	Big Four	65	3.12*
	Non-Big Four	101	2.41*
What proportion of external audit engagements use emerging technologies in the audit process	Big Four	65	2.74*
	Non-Big Four	101	2.22*
Rate your level of satisfaction concerning the use of emerging technologies in your audit firm	Big Four	65	3.65*
	Non-Big Four	101	3.20*

Note(s): *Indicates $p < 0.05$ (two-tailed)

contributes holistically rather than individually to maturity assessment. Similarly, experience in using emerging technologies (Exp) is significantly associated only with technology maturity, while audit firm size remains significantly related to all three measures. The detailed univariate results are presented in Table 10.

4.2.2 Audit evidence collection and maturity assessment. The MANCOVA results (Wilks' lambda) support H2, indicating that the use of emerging technologies in complex audit evidence-gathering procedures is associated with a higher maturity assessment of these technologies. Among the audit evidence variables, using emerging technologies for complex audit evidence collection procedures, such as analytical procedures (AE1) and the inspection of records, documents, and assets (AE2), exhibits the strongest and most significant impact on

Table 8. Hypothesized MANCOVA findings for the effects of key predictors on maturity assessment dimensions

Hypothesis	Predictor(s)	Wilks' lambda	Approx. F	Pr (>F)
H1	ORG 1	0.957	2.366	0.073
	ORG 2	0.369	89.508	<0.001**
	ORG 3	0.922	4.411	0.005**
	ORG 4	0.908	5.302	0.002**
	Exp (control)	0.961	2.099	0.103
	Firm size (control)	0.877	7.338	0.0001**
H2	AE1	0.534	45.413	<0.001**
	AE2	0.787	14.108	<0.001**
	AE3	0.985	0.777	0.508
	AE4	0.983	0.923	0.431
	AE5	0.969	1.690	0.172
	Exp (control)	0.875	7.454	0.0001**
	Firm size (control)	0.765	15.949	<0.001**
H3	FTU1	0.389	83.182	<0.001**
	FTU2	0.966	1.892	0.133
	Exp (control)	0.923	4.429	0.005**
	Firm size (control)	0.770	15.867	<0.001**
H4	SAT	0.658	27.770	<0.001**
	Exp (control)	0.724	20.282	<0.001**
	Firm size (control)	0.737	19.008	<0.001**

Note(s): Significance codes: $**p < 0.01$, $*p < 0.05$
All models assess the multivariate impact on three dependent variables (technology, people, and process) representing Maturity Assessment
ORG 1–4: Organizational Support
AE1-5: Audit Evidence
FTU1-2: Exposure and Frequency of technology use
SAT: Satisfaction

maturity assessment. In contrast, using emerging technologies for less complex audit evidence collection procedures, including observations (AE3), confirmations (AE4), and recalculations and reperformance (AE5), yields insignificant results, suggesting a weaker maturity assessment in these areas. These findings remain significant after controlling for auditors' experience with emerging technologies and audit firm size. Notably, auditors with greater experience (Exp) in using emerging technologies and those in Big Four audit firms exhibit a higher maturity assessment than those with less experience with emerging technologies and those in non-Big Four firms. The detailed MANCOVA results are presented in Table 8.

Next, we conducted a MANOVA, excluding the control variables (audit firm size and experience in using emerging technologies) to examine the direct effect of the five variables related to using emerging technologies to collect audit evidence on maturity assessment. The results remain consistent with the MANCOVA findings, indicating that the use of emerging technologies for analytical procedures and the inspection of records, documents, and assets directly influences maturity assessment. The detailed MANOVA results are presented in Table 9.

Lastly, we conducted a univariate regression analysis (see Table 10) to examine the effect of the five variables related to using emerging technologies to collect audit evidence on each dependent variable. The results consistently indicate that using emerging technologies for analytical procedures (AE1) and for the inspection of records, documents, and assets (AE2) are significant predictors of maturity assessment across all three maturity assessment measures. Similarly, experience in using emerging technologies (Exp) and audit firm size, included as control variables, exhibited a significant effect across all three measures.

Table 9. Multivariate analysis of variance (MANOVA) results for the effects of key predictors on maturity assessment dimensions

Hypothesis	Predictor (s)	Wilks' lambda	Approx. F	Pr (>F)
H1	ORG 1	0.957	2.389	0.071
	ORG 2	0.401	79.197	<0.001**
	ORG 3	0.932	3.863	0.011*
	ORG 4	0.914	5.016	0.002**
H2	AE1	0.620	32.280	<0.001**
	AE2	0.839	10.093	<0.001**
	AE3	0.987	0.701	0.553
	AE4	0.988	0.665	0.575
	AE5	0.975	1.331	0.266
H3	FTU1	0.466	61.386	<0.001**
	FTU2	0.974	1.448	0.231
H4	SAT	0.768	16.288	<0.001**

Note(s): Significance codes: $^{**}p < 0.01$, $^{*}p < 0.05$
All models assess the multivariate impact on three dependent variables (technology, people, and process) representing Maturity Assessment
ORG 1–4: Organizational Support
AE1-5: Audit Evidence
FTU1-2: Exposure and Frequency of technology use
SAT: Satisfaction

Table 10. Univariate regression results for the effects of key predictors on maturity assessment dimensions

Predictor(s)	Technology (β)	People (β)	Process (β)
ORG 1	−0.047	−0.004	0.061
ORG 2	0.304**	0.352**	0.346**
ORG 3	0.158	0.009	0.093
ORG 4	0.190*	0.357**	0.287**
Exp (control)	0.138*	0.037	0.087
Firm size (control)	−0.769**	−0.599**	−0.567**
AE1	0.211**	0.190**	0.215**
AE2	0.221**	0.212**	0.167*
AE3	0.031	0.069	0.084
AE4	0.076	0.077	0.062
AE5	0.004	0.024	0.056
Exp (control)	0.225**	0.145*	0.190**
Firm size (control)	−1.082**	−0.894**	−0.897**
FTU1	0.553**	0.462**	0.511**
FTU2	0.121	0.147	0.132
Exp (control)	0.162**	0.108	0.150**
Firm size (control)	−0.995**	−0.840**	−0.828**
SAT	0.388**	0.345**	0.345**
Exp (control)	0.324**	0.257**	0.310**
Firm size (control)	−1.203**	−1.019**	−1.030**

Note(s): Significance codes: $^{**}p < 0.01$, $^{*}p < 0.05$
Each occurrence of "Experience (Exp)" and "firm size" which are control variables reflect their inclusion in a separate univariate model for each hypothesis (Organizational Support (ORG), Audit Evidence (AE), Exposure and extent of technology use (FTU), and Satisfaction (SAT)

4.2.3 Extent of technology use and maturity assessment. The MANCOVA results (Wilks' lambda) partially support H3, indicating that exposure and frequency of emerging technologies use in the overall audit process is only partially positively associated with a high maturity assessment rating. Of the two variables measuring exposure and frequency of technologies use in the overall audit process, the variable measuring the use of emerging technologies to obtain audit evidence (FTU1) is significantly associated with a high maturity assessment. The result suggests that a high use of emerging technologies to obtain audit evidence is associated with a high maturity assessment. In contrast, the proportion of audit engagements that use emerging technologies in the audit process (FTU2) yields insignificant results, suggesting a weaker association between this proportion and the maturity assessment of emerging technologies. These findings remain significant after controlling for auditors' experience with emerging technologies and audit firm size. Notably, auditors with greater experience (Exp) in using emerging technologies and those in Big Four audit firms exhibit a higher maturity assessment than those with less experience with emerging technologies and those in non-Big Four firms. The detailed MANCOVA results are presented in Table 8.

Subsequently, we conducted a MANOVA, excluding the control variables (audit firm size and experience in using emerging technologies) to examine the direct effect of the two variables related to exposure and frequency of emerging technologies use on maturity assessment ratings. The results remain consistent with the MANCOVA findings, indicating that the use of emerging technologies in obtaining audit evidence is associated with a high maturity assessment rating of these technologies. The detailed MANOVA results are presented in Table 9.

Lastly, we conducted a univariate regression analysis (see Table 10) to examine the effect of the two variables measuring exposure and frequency of technology use on each dependent variable of maturity assessment. The results indicate that the increased use of emerging technologies to obtain audit evidence (FTU1) is consistently associated with a high maturity assessment across all three maturity assessment measures, reinforcing the significant importance and value of adopting emerging technologies to collect audit evidence, which is the bedrock of every audit engagement. However, the extent of use of emerging technologies in the overall audit engagement is consistently a weak predictor ($p > 0.05$) of maturity assessment in all three maturity assessment measures. Similarly, experience in using emerging technologies (Exp) and audit firm size, included as control variables, exhibited a significant effect across all three measures, except for the people measure, where experience exhibits a weak effect.

4.2.4 Satisfaction and maturity assessment. The MANCOVA results (Wilks' lambda) support H4, indicating that satisfaction with emerging technologies use (SAT) is positively associated with a high maturity assessment rating. The results suggest that increased satisfaction with emerging technology use is associated with a high maturity assessment of these technologies. These findings remain significant after controlling for auditors' experience with emerging technologies and audit firm size. Notably, auditors with greater experience (Exp) in using emerging technologies and those in Big Four audit firms exhibit a higher maturity assessment than those with less experience with emerging technologies and those in non-Big Four firms. The detailed MANCOVA results are presented in Table 8.

Subsequently, we conducted a MANOVA, excluding the control variables (audit firm size and experience in using emerging technologies) to examine the direct effect of satisfaction with emerging technology use on maturity assessment ratings. The results remain consistent with the MANCOVA findings, indicating that satisfaction with emerging technologies use is strongly associated with a high maturity assessment rating of these technologies. The detailed MANOVA results are presented in Table 9.

Lastly, we conducted a univariate regression analysis (see Table 10) to examine the effect of satisfaction with emerging technology use on each dependent variable of maturity assessment. The results indicate that satisfaction with emerging technology use (SAT) is consistently associated with a high maturity assessment across all three maturity assessment measures.

Similarly, experience in using emerging technologies (Exp) and audit firm size, though treated as control variables, remained significant across all three measures.

5. Discussions

Audit firms are generally positioned at a moderate level of technology adoption (the developing and repeatable stages across people, process, and technology), indicating progress in maturity that may accelerate further adoption and address the current slow uptake of emerging technologies (Austin *et al.*, 2021; Eilifsen *et al.*, 2020; Gepp *et al.*, 2018; Salijeni *et al.*, 2019). According to Smidt's (2016) framework, this suggests progress toward enhanced adoption, with firms beginning to establish structured data access procedures and adopt basic functionalities of emerging technologies, but still falling short of full integration. The descriptive findings support this interpretation: auditors expressed neutrality regarding formal policies and procedures, staff training, greater use of emerging technologies in client data analysis, audit evidence collection, and fraud detection. Furthermore, their limited use of these technologies in core audit procedures (inspection, observation, confirmation, recalculation, and reperformance) underscores that audit firms are adopting only basic functionalities rather than achieving full integration. Most data analytics are still performed in Excel, with emerging technologies applied primarily to analytical procedures, while overall satisfaction with these technologies remains moderate. These patterns are consistent with the moderate phase of maturity (developing and repeatable stages), where processes are becoming more standardized but adoption remains limited in scope. Firms are increasingly using descriptive (what happened?) and diagnostic (why did it happen?) analytics to refine audit procedures and obtain sufficient appropriate audit evidence (Barr-Pulliam *et al.*, 2022), yet advanced practices such as predictive analytics and continuous auditing remain rare. From a people perspective, auditors are acquiring relevant skills, and some possess advanced expertise, but most firms continue to rely on technology specialists, indicating a transitional phase—beyond experimentation but not yet fully integrated.

The overall maturity assessment at the moderate stage, together with both Big Four and non-Big Four firms transitioning to higher maturity levels of technology adoption, suggests a future trajectory toward enhanced adoption of emerging technologies. This increased adoption aligns with post-pandemic studies (e.g. Altiero *et al.*, 2024; Fotoh, 2025) that underscore how the pandemic has positively accelerated technology adoption by enabling auditors to work remotely (Lorentzon *et al.*, 2024). Therefore, the observed improvement in technology adoption may have been influenced by a shift in auditors' attitudes, driven by their experience of the dynamic capabilities these technologies offered during the pandemic (Fotoh *et al.*, 2025).

Despite the overall finding that audit firms are in the moderate phase of technology adoption, notable differences exist between Big Four and non-Big Four firms. The non-Big Four firms fall below the moderate threshold (in the advanced ad hoc stage and transitioning toward the developing phase), while the Big Four are slightly above the moderate stage (in the advanced repeatable stage and transitioning toward the embedded phase). This is supported by the findings that Big Four firms tend to have more formal guidelines and procedures for adopting emerging technologies, provide training to guide staff in their proper application, analyze more client data using these technologies, and rely on them for obtaining audit evidence and detecting fraudulent activities. They also report more extensive use of these technologies in performing analytical procedures and express higher satisfaction levels compared to their non-Big Four counterparts. These differences, along with the higher maturity assessments reported by Big Four auditors, align with prior literature suggesting that Big Four firms are more likely to perceive and rate these technologies favorably (e.g. Janvrin *et al.*, 2008; Lowe *et al.*, 2018). This tendency is potentially due to the complexity of their client portfolios, necessitating their adoption and greater exposure to the potential efficiencies and effectiveness these technologies offer. In contrast, non-Big Four firms, which typically serve less complex clients and operate with fewer resources, may adopt these technologies more slowly (Janvrin *et al*., 2008, 2009; Lawrence *et al*., 2011; Lowe *et al*., 2018).

Overall, the hypothesized findings suggest the crucial role of enhanced organizational support in facilitating maturity assessment, which is necessary for realizing the touted benefits of emerging technologies—specifically, enhanced audit efficiency, effectiveness, and audit quality (e.g. Barr-Pulliam *et al*., 2022; Cao *et al*., 2015; Christ *et al*., 2021). The strong association observed between formal guidelines and procedures for the adoption of emerging technologies, as opposed to the weaker maturity assessment observed when adoption is informal and left to the individual discretion of the engagement audit partner or audit team, suggests that formalized guidelines and procedures reinforce the legitimacy of these technologies. Such guidelines are associated with auditors developing the necessary skills and competence to use these technologies effectively. Moreover, they facilitate structured processes that support adoption and are associated with the perceived efficiency and suitability of these technologies in performing audit tasks. These findings align with Kim and Kankanhalli's (2009) argument that organizational support, through structured policies, actions, and resources, creates a conducive environment for successful technology adoption. This observation may also explain why the control variable, experience in using emerging technologies, does not significantly impact overall maturity assessment. It suggests that individual auditors' familiarity with emerging technologies may be less influential in shaping firm-wide technology maturity than formal firm-wide guidelines and procedures. Therefore, audit firm structures appear to play a more decisive role than individual expertise in assessing the maturity of emerging technologies, underscoring the need for policy-driven, firm-wide initiatives to enhance emerging technology maturity.

In addition to formal guidelines and procedures, organizational training on emerging technologies reinforces the importance of technological skills and competence development, as underscored by contemporary studies (Igou *et al*., 2023; Vitali and Giuliani, 2024) in driving emerging technology maturity. Partially aligning with Fotoh and Mugwira (2024), the findings suggest that investment in continuous learning opportunities for auditors on emerging technologies is associated with their operational competence development (people maturity). This, in turn, likely facilitates the development of structured processes that support the adoption of emerging technologies in the audit process (process maturity) and fosters positive perceptions of these technologies' suitability and efficiency in performing audit tasks. However, the impact of organizational training on maturity assessment appears significant only when combined with both formal and informal guidelines and procedures, and using emerging technologies to perform data analysis. It is not individually significant when considered separately for each maturity assessment dimension (people, process, and technology). This finding suggests that organizational training alone does not lead to emerging technology maturity. Instead, such training and guidance must be reinforced by formal organizational guidelines and procedures, along with the actual use of these technologies for data analysis in the audit process.

Furthermore, the finding that greater reliance on emerging technologies for data analysis over traditional audit methods is associated with higher levels of emerging technological maturity underscores the critical role of embedding these technologies into audit workflows. This integration potentially contributes to auditors' skill development and the establishment of structured processes that facilitate the adoption of these technologies. It also enhances perceptions of their suitability and efficiency in audit processes, which could ultimately lead to the use of advanced analytics (descriptive, diagnostic, predictive, and prescriptive) associated with enhanced audit efficiency and effectiveness (e.g. Barr-Pulliam *et al*., 2022). Unlike traditional audit methods, emerging technologies can analyze both structured and unstructured data (Richins *et al*., 2017; Sun, 2019), which may explain the higher maturity assessment ratings of these technologies when used for data analysis.

The finding that the use of emerging technologies in performing complex audit evidence-gathering procedures (such as analytical procedures and inspection of records, documents, and assets) is associated with a higher maturity assessment suggests that these technologies enhance efficiency by performing time-consuming and complex audit procedures and enabling auditors to focus on judgment-oriented tasks, aligning with existing literature (Barr-Pulliam *et al*., 2022, 2024; Christ *et al*., 2021). It is noteworthy that analytical procedures play a critical role in the planning, substantive, and review phases of audits (AS No. 2110, PCAOB, 2010b; AS No. 2810, PCAOB, 2010c; AS No. 2305, PCAOB, 2010d). Thus, the positive association between emerging technologies and analytical procedures suggests that auditors possess the necessary skills and competence to use these technologies effectively, that structured processes exist to facilitate their adoption, and that these technologies are well-suited for performing such tasks. These findings are consistent with Eilifsen *et al*. (2020), who reported that audit partners and managers perceive themselves as possessing the requisite knowledge for emerging technologies such as advanced data analytics. From a process perspective, while contemporary studies (e.g. Austin *et al*., 2021; Eilifsen *et al*., 2020; Gepp *et al*., 2018; Salijeni *et al*., 2019) highlight the slow adoption of emerging technologies in audits, our findings suggest that the participating auditors believe that processes are in place to facilitate the adoption of these technologies. This raises the question: why is the adoption rate slow despite established processes? From a technological perspective, our results align with prior studies emphasizing the role of emerging technologies, such as advanced data analytics, in enhancing risk assessment, full population testing, anomaly detection, control assessment, and compliance monitoring (e.g. Brown-Liburd *et al*., 2015; Cao *et al*., 2015; Earley, 2015; Salijeni *et al*., 2019; Schneider *et al*., 2015).

Similarly, for inspection of records, documents, and assets, auditors report a higher maturity assessment, indicating confidence in their skills and competence, the existence of structured processes, and the suitability and efficiency of these technologies for such tasks. From a technological standpoint, this partially aligns with contemporary studies (e.g. Appelbaum and Nehmer, 2017; Christ *et al*., 2021; Fotoh, 2025) that highlight the potential of advanced technologies in facilitating complex procedures such as inspections.

Conversely, the insignificant association between maturity assessment and simple audit evidence-collection procedures (such as observation, confirmation, recalculation, and reperformance) suggests that these tasks place fewer demands on auditors' technological skills and competence, organizational processes, and emerging technology adoption. Given the relatively low complexity of these procedures and the possibility of using less complex technologies such as cloud-based software, Microsoft Teams, and Zoom (e.g. Altiero *et al*., 2024; Fotoh *et al*., 2025), such procedures may not warrant the substantial investments required for emerging technology adoption, training, and process redesign. This is particularly the case because auditors tend to adopt technologies only when they perceive strong value (Janvrin *et al*., 2008, 2009). The lower maturity assessment for these procedures may also reflect a preference among auditors for performing them manually, which aligns with evidence that, in some instances, auditors prefer traditional manual procedures over technologies (Fotoh, 2025). For example, observation, which involves evaluating client activities and control environments, heavily relies on auditors' professional skepticism and judgment, potentially explaining the low maturity assessment. Confirmation, often requiring third-party validation of account balances or transactions, may be perceived as straightforward and better suited to manual performance. Similarly, recalculations and reperformance are typically based on structured accounting records, which human auditors can efficiently assess, even though emerging technologies can perform such tasks. Overall, the low maturity assessment for these procedures may reflect two key factors: (1) their relatively simple nature, which does not necessitate the high investment required for emerging technology adoption, and (2) a prevailing preference for human auditors to perform these procedures.

The findings indicate that exposure to and frequent use of emerging technologies are not only associated with technology acceptance (see Fotoh and Mugwira, 2024) but are also partially linked to higher maturity assessment ratings, particularly in obtaining audit evidence. This suggests that increased exposure to and usage of emerging technologies results in enhanced auditors' skills and competence in conducting audit evidence-gathering procedures using these technologies. Additionally, frequent use potentially leads to the development of structured processes that support the adoption of these technologies in auditing. Moreover, it reinforces auditors' perception of these technologies as suitable and efficient for obtaining audit evidence. These findings extend prior literature (e.g. Davis *et al.*, 1989; Kim *et al.*, 2009) by demonstrating that the frequency of technology use and exposure to its features influence not only its acceptance and adoption rate but also its overall maturity assessment, particularly concerning audit evidence collection.

On the other hand, a broader proportion of audit engagements utilizing emerging technologies does not correlate with higher maturity assessment ratings. This suggests that auditors may lack the in-depth skills and competencies required to effectively apply these technologies across all audit procedures, reinforcing the need for technological upskilling and competence development to facilitate effective adoption (Coderre, 2015; Igou *et al.*, 2023; Vitali and Giuliani, 2024). Additionally, many audit firms may have insufficient processes to facilitate and support their widespread adoption, echoing findings that organizational readiness and process maturity are crucial to realizing emerging technology maturity (Coderre, 2015). Furthermore, some emerging technologies may not be perceived as sufficiently suitable or efficient for certain audit procedures, aligning with evidence that adoption varies based on task complexity (Cooper *et al.*, 2019, 2022; Moffitt *et al.*, 2018). For instance, RPA tools are more efficient for structured and repetitive tasks than for complex tasks requiring auditors' judgment (Cooper *et al.*, 2019, 2022; Moffitt *et al.*, 2018). Collectively, these factors likely contribute to the insignificant association between the proportion of audits conducted using emerging technologies and overall maturity assessment ratings. Thus, a higher maturity assessment appears more closely linked to the performance of specific audit procedures rather than the broad expansion of emerging technologies across all audit procedures.

The study underscores the critical role of satisfaction with emerging technologies as a key factor in achieving higher overall maturity assessment ratings. The findings suggest that satisfaction with these technologies is associated with the development of auditors' skills and competence, the establishment of structured processes to support their adoption, and the perception that these technologies are efficient and suitable for audit procedures. This study extends the existing literature by demonstrating that satisfaction with emerging technologies is not only linked to the intention to continue using them (e.g. Deng *et al.*, 2010; Kuo *et al.*, 2009; Liu *et al.*, 2011) and their actual use (e.g. Ajzen and Fishbein, 1980) but also contributes to higher overall maturity ratings. Consequently, aligning emerging technologies with audit procedures may encourage auditors to develop the necessary skills and competence, facilitate the establishment of processes that support adoption, and enhance perceptions of their efficiency and suitability in audit engagements.

Additionally, except for Hypothesis 1, where experience with emerging technologies does not significantly impact maturity assessment and is only associated with technological maturity, the findings from the other three hypotheses suggest that auditors with more experience using emerging technologies and those in Big Four audit firms report higher maturity assessments than their less-experienced and non-Big Four counterparts. This finding aligns with the rationale that exposure to and use of emerging technologies likely familiarize auditors with their touted efficiency and effectiveness benefits, as asserted by prior research (e.g. Barr-Pulliam *et al.*, 2022; Cao *et al.*, 2015; Christ *et al.*, 2021), potentially leading to higher maturity assessments. However, achieving such higher maturity levels requires auditors to possess the requisite skills and competence to use these technologies effectively (e.g. Igou *et al.*, 2023; Vitali and Giuliani, 2024).

Figure 1 illustrates the drivers of emerging technology maturity in external audits, based on the findings of this study. The outermost layer highlights the role of the external audit environment, particularly proactive audit standards and regulatory guidelines, which serve as critical enablers of technology maturity. These external standards provide legitimacy and direction for audit firms to adopt emerging technologies. Within this broader context, the

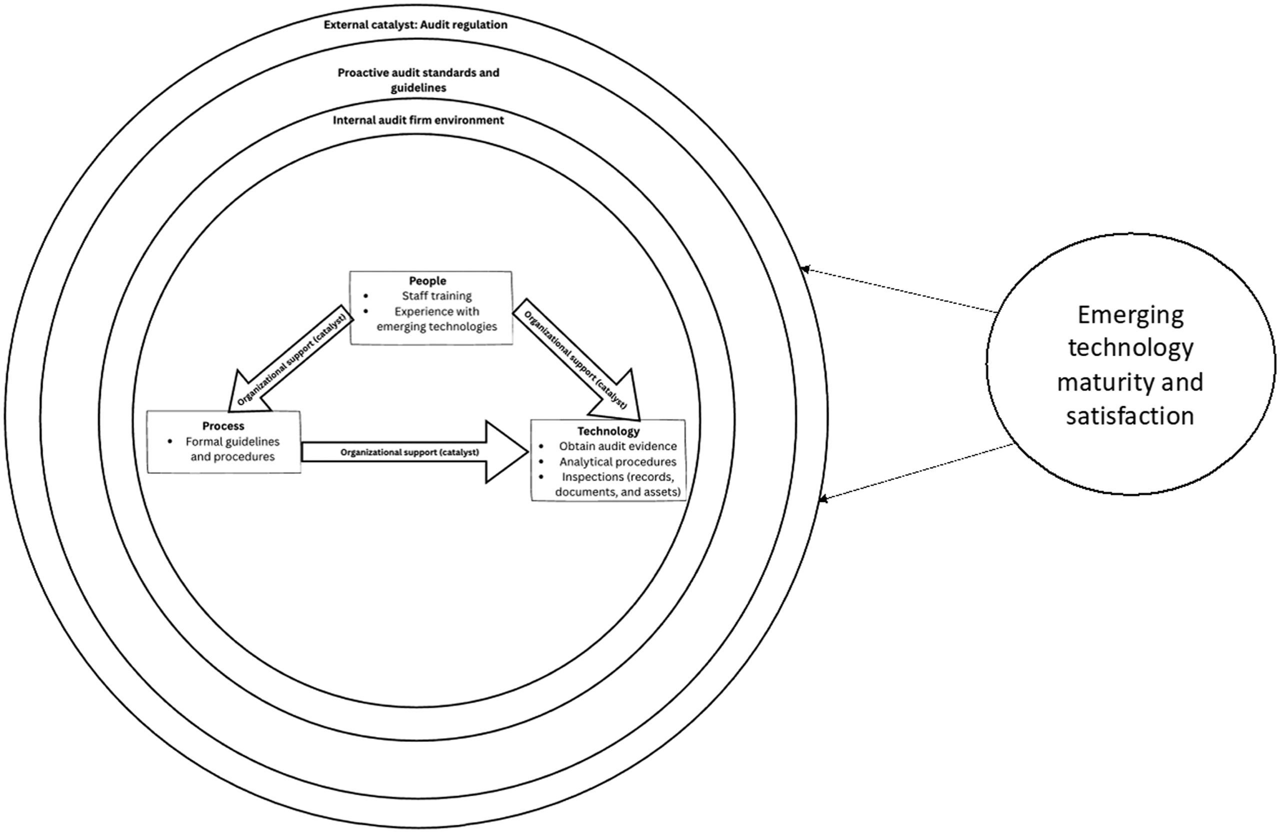

Figure 1. Drivers to emerging technology maturity in external audits

internal audit environment must adapt across three key dimensions, as represented by the triangle in the center of the figure. First, from a people perspective, staff training and experience with emerging technologies are essential to support maturity. Second, from a process standpoint, audit firms need to develop formal internal guidelines and procedures for using these technologies, ideally aligned with external regulatory expectations. Third, from a technology perspective, emerging technologies are relevant in particularly evidence-collection procedures such as analytical procedures and the inspection of records, documents, and assets. Organizational support acts as a necessary catalyst for these internal adaptations. When adjustments in people, process, and technology are supported and aligned, they contribute to the overall maturity of emerging technologies within the external audit function, and satisfaction with these technologies.

6. Conclusions

The objective of this study is to examine audit firms' maturity in adopting emerging technologies across three dimensions: people, process, and technology, and to identify the factors that shape this maturity. To achieve this objective, we employed a maturity assessment framework centered on three key dimensions: technology, people, and processes. The findings show that participating auditors generally perceive their firms to be at a moderate stage of technology adoption (developing and repeatable) across all three dimensions: people, process, and technology. However, comparative results reveal that Big Four firms are perceived to exhibit higher maturity levels, suggesting a transition from the repeatable to the embedded phase. In contrast, non-Big Four firms are perceived as progressing from the ad hoc to the developing stage, remaining below the moderate maturity threshold. One explanation for the higher maturity levels among Big Four firms is their greater availability of resources, stemming from large investments and organizational capital. Moreover, the complexity and scale of their client portfolios, coupled with reputational incentives to lead in technological innovation, create external pressures that encourage the adoption and integration of emerging technologies.

Additionally, the findings suggest that organizational support, such as formal guidelines, training programs, and the use of emerging technologies for data analysis, is positively associated with higher maturity levels. Meanwhile, informal and discretionary adoption by individual partners or teams has a weaker impact. Similarly, using emerging technologies in complex audit evidence-gathering procedures (e.g. analytical procedures; and inspection of records, documents, and assets) is linked to higher maturity, whereas using them for simple audit evidence-gathering procedures (e.g. observation, confirmation, recalculation, and reperformance) shows no significant association with maturity levels. Exposure to and frequent use of emerging technologies are linked to higher maturity levels only when applied specifically to audit evidence collection, not broader audit activities.

The findings further reveal that satisfaction with emerging technologies, along with prior experience in their use, correlates with higher maturity levels. Notably, significant disparities exist between Big Four and non-Big Four firms. Unlike non-Big Four firms, Big Four firms are more likely to have formalized guidelines and procedures, invest in staff training, use emerging technologies more extensively for client data analysis than traditional audit methods, and apply these technologies to collect audit evidence and detect fraudulent activities, which contribute to their higher maturity assessments. Notably, the results indicate a balanced perception of maturity across the different aspects. Since these aspects are interdependent, the development within both Big Four and smaller firms appears to be incremental. This suggests that the successful use of emerging technologies requires a balance among the different dimensions, along with functional support and clear guidance.

These findings have several implications for audit practice and research. Organizational support is not only crucial in addressing resistance and the slow adoption of emerging technologies (Fotoh and Mugwira, 2024), but it also plays a significant role in advancing technological maturity. To move beyond the developing stage, audit firms must develop and implement formal guidelines and procedures for technology adoption, doing so strengthens both the "process" dimension of the maturity framework and the perceived legitimacy of emerging technology use, compared to informal and discretionary adoption by individual partners. The need for firm-wide guidelines also highlights a broader call for proactive regulatory guidance regarding the adoption of emerging technologies. Many audit firms hesitate to adopt these technologies due to enhanced regulatory scrutiny and potential legal liabilities following audit failures (Austin *et al.*, 2021; Barr-Pulliam *et al.*, 2022; Gepp *et al.*, 2018). Thus, this study supports prior calls for a proactive regulatory approach (e.g. Austin *et al.*, 2021; Igou *et al.*, 2023), which could catalyze the development of organizational procedures and policies aligned with formal regulatory expectations. From a "people" perspective, enhanced maturity can be achieved through firm-wide initiatives that build competence and confidence in adopting emerging technologies. From a "technology" perspective, maturity can be advanced by aligning emerging technologies with audit processes, particularly in the execution of complex audit evidence-gathering procedures. This alignment enables auditors to focus more on judgment-oriented tasks, thereby potentially enhancing audit quality.

In light of these findings, several avenues for future research emerge. While the audit industry has made notable strides in adopting emerging technologies, the persistent gap between Big Four and non-Big Four firms warrants further investigation. Future research could explore strategies to enhance technology adoption among non-Big Four firms, particularly in light of their unique resource constraints. This is especially important for the survival of non-Big Four firms, which play a critical role in meeting the diverse demand for audit services across various types of firms. The relatively conservative levels of satisfaction expressed by auditors suggest a sense of cautious optimism toward the use of emerging technologies. This opens up opportunities for further research into the behavioral and contextual factors influencing auditor satisfaction, acceptance, and long-term adoption of emerging technologies in audits. Finally, given that this study focuses on auditors' perceptions of technology maturity, future research could extend these findings by examining actual maturity levels within audit firms and comparing them with perceived levels. As audit firms navigate the rapidly developing digital environment, understanding and advancing knowledge of emerging technology maturity remains critical, with important implications for enhancing audit quality and the overall relevance of the audit function.

This study has some limitations. First, it relies on self-reported data, which may be subject to personal bias or misperceptions, potentially constraining the accuracy of maturity assessments. This raises the possibility that auditors' perceptions of technology maturity differ from actual maturity. Future research could incorporate objective performance metrics or direct assessments of emerging technologies. Second, the study adopts a cross-sectional design, capturing a single point in time. As a result, the findings do not account for how maturity may evolve as technologies diffuse or as audit firms' strategies change. Longitudinal designs would therefore provide deeper insights into trajectories of technology maturity. Finally, the study does not differentiate between types of emerging technologies (e.g. AI, blockchain, data analytics), which may vary substantially in maturity. While the objective was to obtain a comprehensive perspective of overall maturity, this approach may mask significant differences across technologies. Future studies could explore technology-specific maturity levels to provide more granular insights.

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Appendix

Table A1. Assumption testing for MANCOVA

Diagnostic check results
For the MANCOVA with Organizational Support as the independent variable, Box's M test was non-significant, Box's M = 41.039, F(30, 10476.552) = 1.273, $p = 0.145$, indicating homogeneity of covariance matrices. Levene's tests for equality of variances were also non-significant for all three dependent variables: technology ($F(5, 160) = 0.918$, $p = 0.471$), people ($F(5, 160) = 0.597$, $p = 0.702$), and process ($F(5, 160) = 1.751$, $p = 0.126$), suggesting homogeneity of variances. The interaction between Organizational Support and Experience was non-significant, Wilks' $\Lambda = 0.944$, $F(6, 314) = 1.532$, $p = 0.167$, partial $\eta^2 = 0.028$, indicating that the relationship between the covariate and the dependent variables did not significantly differ across groups. Therefore, the assumptions for MANCOVA were met
For the MANCOVA with Audit Evidence as the independent variable, Box's M test was non-significant, Box's M = 37.408, F(30, 6495.518) = 1.143, $p = 0.269$, indicating homogeneity of covariance matrices. Levene's tests were non-significant for all three dependent variables: technology ($F(5, 160) = 1.502$, $p = 0.192$), people ($F(5, 160) = 2.138$, $p = 0.064$), and process ($F(5, 160) = 1.908$, $p = 0.096$), suggesting homogeneity of variances. The interaction between Audit Evidence and Experience was also non-significant, Wilks' $\Lambda = 0.966$, $F(6, 314) = 0.924$, $p = 0.478$, partial $\eta^2 = 0.017$, indicating that the relationship between the covariate and the dependent variables did not differ across groups. Therefore, the assumptions for MANCOVA were met
For the MANCOVA with Exposure and Frequency of Emerging Technology Use as the independent variable, Box's M test was significant, Box's M = 56.873, F(30, 18682.435) = 1.776, $p = 0.006$, indicating a violation of the assumption of equal covariance matrices. However, Levene's tests were non-significant for all dependent variables: technology ($F(5, 160) = 1.032$, $p = 0.401$), people ($F(5, 160) = 1.343$, $p = 0.249$), and process ($F(5, 160) = 1.320$, $p = 0.258$), suggesting homogeneity of variances. Additionally, the interaction between Exposure and Frequency of Emerging Technology Use and Experience was non-significant, Wilks' $\Lambda = 0.961$, $F(6, 314) = 1.045$, $p = 0.478$, partial $\eta^2 = 0.020$. Although Box's M was significant, all other assumptions were satisfied; thus, the assumptions for MANCOVA were considered generally met.
For the MANCOVA with Satisfaction as the independent variable, Box's M test was significant, Box's M = 74.429, F(30, 2146.303) = 2.210, $p = 0.001$, indicating a violation of the assumption of homogeneity of covariance matrices. However, Levene's tests were non-significant across all dependent variables: technology ($F(5, 160) = 0.702$, $p = 0.623$), people ($F(5, 160) = 0.551$, $p = 0.737$), and process ($F(5, 160) = 1.079$, $p = 0.374$), supporting the assumption of equal variances. The interaction between Satisfaction and Experience was also non-significant, Wilks' $\Lambda = 0.932$, $F(6, 314) = 1.881$, $p = 0.084$, partial $\eta^2 = 0.035$, suggesting that the covariate did not differentially affect the dependent variables across satisfaction groups. While Box's M was significant, the other assumptions were met, and the assumptions for MANCOVA were generally considered satisfied

Notes

1. Emerging technologies, as described by Rotolo *et al.* (2015), are characterized by their groundbreaking innovation, rapid development, significant impact, and inherent uncertainty. Similarly, the International Federation of Accountants (IFAC, 2020) notes that emerging technologies include advanced tools such as artificial intelligence, big data analytics, blockchain, robotic process automation, cloud computing, drones, social networks, and digital payment systems, which are significantly reshaping auditing practices. This study adheres to this definition and range of emerging technologies. Additionally, while this manuscript considers artificial intelligence as an emerging technology, it does not specifically address generative AI or large language models, as these technologies were not prevalent in auditing at the time of data collection.

2. There are several fundamental differences between internal audit and external audits. These differences include scope and objectives (internal audits primarily evaluates and improves internal control systems, risk management and operational efficiency whilst external audits provides an independent assessment of an organizations financial statements), regulatory requirements (internal auditing have broader mandate that includes compliance with internal procedures whilst external audits focuses on compliance with external regulations and applicable financial reporting framework).

3. The institutional Review Board (IRB) of a university affiliated with one of the coauthors approved this study.
4. SUNET is a data collection platform provided by the Swedish Research Council, which ensures its use aligns with national data protection and ethical guidelines.
5. Our response rate is in line with recent maturity assessment studies (e.g. Wu and Huang, 2025) and meets the reliability threshold of Fosnacht *et al.* (2017).
6. These highly experienced auditors are the most suitable group since they are expertise in the profession and therefore can offer valuable industry insights and their contribution can result in a robust evaluation of how emerging technologies are adopted into the audit process.
7. The percentages for other emerging technologies are shown in Table 2. Respondents who selected "None" indicated that their firms do not use emerging technologies, although they still made use of alternative forms of technology.

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