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How Do Internal Auditors Assess the Importance and their Knowledge of Innovative Technologies and what are Major Knowledge-Gaps?

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Abstract: New information technology (IT) can add value to internal auditing. Accordingly, we examine the future importance of digital innovations and the related current knowledge from a practitioner's perspective. Based on a literature review, and interviews with professionals, we identified 19 applications relevant for a deeper analysis. Afterwards, we conducted a quantitative study in three countries (Germany, Austria, and Switzerland) and received 143 usable responses. Study participants evaluated 15 tools as particularly important. Our results show that self-assessed technical capabilities for most IT are low, even for those with a potentially high future relevance, e.g., data mining. Complementary regression analyses revealed that experienced internal auditors, younger subjects, and respondents outside the financial industry perceive advanced IT as more important. In general, men rated their own knowledge higher than female participants. Comparing relevance and knowledge, we find a notable discrepancy across the toolkit, which is much greater for women. Increased efforts by (top) managers, academics, and regulators seem essential to close this gap.

Keywords: big data, digital innovations, internal auditing, IT importance, IT knowledge, technology-based audit techniques (TBATs)

Wie beurteilen Interne Revisoren die Bedeutung von und ihre Kenntnisse zu innovativen Technologien und wo bestehen wesentliche Kenntnislücken?

Zusammenfassung: Der Einsatz innovativer IT in der Innenrevision kann nützlich sein. Vor diesem Hintergrund werden die zukünftige Bedeutung digitaler Technologien und die aktuellen Kenntnisse aus dem Blickwinkel Interner Revisoren untersucht. Auf der Grundlage einer Durchsicht der einschlägigen Literatur und von Interviews mit Internen Revisoren konnten 19 Technologien identifiziert werden, die Gegenstand einer Umfrage waren. An dieser nahmen Berufsangehörige aus drei Ländern (Deutschland, Österreich und Schweiz) teil. Es ergaben sich 143 auswertungsfähige Antworten. Die Untersuchungsteilnehmer schätzen 15 Technologien als besonders wichtig ein. Die Kenntnisse der befragten Internen Revisoren sind für die meisten IT hingegen gering, auch für solche mit vermutlich besonders hoher künftiger Bedeutung, wie z.B. Data Mining. Ergänzende Regressionsanalysen zeigen, dass erfahrenere Revisoren, jüngere Teilnehmer und Befragte,

die nicht in der Finanzbranche tätig sind, neuartige Technologien für wichtiger erachten. Männliche Revisoren verfügen über bessere IT-Kenntnisse als ihre weiblichen Pendants. Schließlich zeigt sich eine hohe Diskrepanz zwischen künftiger Bedeutung und aktuellen Kenntnissen. Somit bedarf es besonderer Anstrengungen, insbesondere des Berufsstands, um diese Lücke zu schließen.

Stichworte: Big Data, digitale Innovationen, Innenrevision, IT-Bedeutung, IT-Kenntnisse, technologiebasierte Prüfungsmethoden

1. Introduction

Internal auditing ensures high-quality governance (e.g., Prawitt et al., 2009; Ege, 2015; Abbott et al., 2016; Trotman & Duncan, 2018; Eulerich et al., 2022b) and serves as an essential safeguard against organizational risk (Carcello et al., 2020), often relying on the accounting information system (AIS) (Gramling et al., 2004). With the introduction of innovative technologies in recent years, corporate AIS has evolved significantly (Bhimani & Willcocks, 2014). Businesses are employing digital solutions more than ever, making it difficult to conduct an audit without electronic aids (Moffit & Vasarhelyi, 2013). Practitioners will only be able to provide reasonable assurance through improved gathering (Jans et al., 2014; Pickard et al., 2020), improved modeling (Ballou et al., 2021), and improved displaying (Baaske et al., 2023) of data. Thus, internal auditors must acquire sufficient knowledge of information technology (IT) and technology-based audit techniques (TBATs) to perform their assigned work (IIA, 2017a, sec. 1210.A3).

However, leveraging sophisticated IT often requires complex techniques that professionals need to become more familiar with (Li et al., 2018; Emett et al., 2023b). For example, audit analytics normally involve advanced statistical operations (Bi & Cochran, 2014), so mastering these types of technologies could be challenging. Indeed, expanding internal audit digital capabilities has become a top priority for organizations (Christ et al., 2021b; Protiviti, 2023), as relatively few of them report that their internal audit team understands the importance of innovative IT (Eulerich, 2023). Prior application-based papers addressed the adoption of drones (for asset measurement; Appelbaum & Nehmer, 2017, Christ et al., 2021a), process mining (for continuous auditing; Jans & Hosseinpour, 2019; Jans & Eulerich, 2022) or robotic process automation (for well-defined, highly repetitive tasks; Bakarich & O'Brien, 2021; Eulerich et al., 2022a; Eulerich et al., 2024; Seidenstein et al., 2024), but there are many other aids to explore and explain. As a result, the pace of growth and scale of implementation of these tools is not keeping pace with developments of the underlying businesses (Weidenmier & Ramamoorthi, 2006). This represents a substantial gap in the literature.

Examining a new generation of technology in the context of internal auditing contributes to broader discourse because novel aids are only effective if they meet occupational goals (Goodhue & Thompson, 1995). If the IT portfolio evolves, internal auditors should respond by adapting their toolbox. Therefore, we see the need to identify future key technologies, figure out gaps, and to provide a benchmark concerning presumably relevant IT. Second, to be efficient and effective, the internal audit function (IAF) must acquire digital solutions and enable their personnel to successfully use these tools (Eulerich et al., 2023). As Janvrin et al. (2008) noted nearly two decades ago (in an external audit setting), the user creates advantages, not the innovations themselves.[1] Accordingly, the prerequisites for IT competence consist of two parts: (1) An appropriate infrastructure of important aids and (2) many knowledgeable users (Zhu & Kraemer, 2005; Austin et al., 2021). In times of strict budget constraints and when it is challenging to hire technical experts (Christ et al., 2021b), the fit between IT importance and IT knowledge becomes even more crucial.

Of course, TBATs also benefit public accountants, and research activity in this area is more advanced (e.g., Janvrin et al., 2008; Ismail & Abidin, 2009; Salijeni et al., 2019; Feliciano & Quick, 2022). However, due to differences in baseline conditions, prior findings may not be necessarily transferable to internal auditing (Li et al., 2018). On the one hand, internal auditors perform a broader range of tasks (Anderson et al., 2012), which could lead to broader use of digital solutions. On the other hand, they have easier access to data (Schneider et al., 2015), implying earlier adoption of emerging IT. Regulatory constraints are less for internal auditors. Therefore, their mindset regarding technological innovations is more open, resulting in a continuous adaption of technology and related continuous education. Thus, since the regulation of internal auditing is less strict than those of external auditing (Krahel & Titera, 2015), exploring various tools seems even more plausible. Against this background, we pose four research questions:

(1) What is the future relevance of innovative TBATs in internal auditing (= IT importance)?
(2) What is the current state of internal auditors' knowledge in innovative TBATs (= IT knowledge)?
(3) What are the gaps between future relevance and current internal auditors' knowledge concerning innovative TBATs (= IT gap)?
(4) What internal auditors' demographics affect IT importance, IT knowledge, and IT gap concerning innovative TBATs (= impact factors)?

To provide answers to these four questions, we identified 19 technologies with disruptive potential (Christensen, 2013) and embedded them into a quantitative research design. For each selected tool, participants from three countries (Germany, Austria, and Switzerland) were asked to rate (1) its future relevance and (2) their current related knowledge. The sample includes 143 usable responses. Our participants assume that 15 TBATs will be of (greater) importance. Unsurprisingly, the current knowledge of internal auditors lags behind the future relevance of the technologies under investigation. However, our study results also inform about the size of such gaps, which could be important information for firms' decision-makers. Years of experience significantly impact IT importance, as do age and industry-specific tasks. Gender influences both IT knowledge and the IT gap. Ergo, perceptions about the relevance of future technology are lower among less experienced and older professionals, especially in financial services. Women currently have lower technical skills, which leads to significant efforts in aligning relevance and knowledge.

Our empirical investigation examines a range of future technologies and compares their relative importance from the perspective of internal auditors. We respond to recent calls for practice-relevant research (Rajgopal, 2020; Burton et al., 2022). Given the high cost of IT adoption (Eulerich et al., 2023), the findings can help (top) managers make effective

1 In general, innovations could be defined as the realization of a novel solution to a specific problem, especially through the introduction of a new technology (e.g., Damanpour, 1991; Christ et al., 2024).

investments. In addition, our analyses indicate low levels of knowledge in most innovations. This requires adequate academic focus and continuous training activities (Chang & Hwang, 2003; Aldredge et al., 2021). Because of concerns about internal auditors' value provision (Eulerich & Eulerich, 2020), technical skills must change substantially in the coming years (Tang et al., 2017). Since the IT gap is significantly larger for females, we propose a holistic approach to better prepare them for a digital environment. As staffing remains critical (Christ et al., 2021b), professional bodies, scholars, and standard setters could align their efforts (Jackson et al., 2022) to attract more women to IT-enabled internal auditing. Even though gender has not been a major topic in prior audit literature (Haynes, 2017), the use of IT should no longer be considered a 'male thing' (Encinas-Martín & Cherian, 2023; WEF, 2023).

This paper proceeds as follows. Section two describes the status of previous research. Then, the research design is explained in section three, while empirical findings are reported in section four. Section five concludes with a summary, a discussion of limitations, and suggestions for future research.

2. Literature Review

To understand the spread of novel IT solutions and its practical relevance, scholars have explored various aspects. For structuring previous findings, we draw on Bonner's judgment and decision-making model (Bonner, 2008). Her framework focuses on three dimensions: the person, the task, and the environment. This approach is applicable because research in information systems suggests that personal attitudes towards technology should not be considered in isolation but in conjunction with other factors (e.g., Venkatesh et al., 2003). These causal relationships are complex; thus, a holistic view is needed to contextualize innovations in relation to the nature, timing, scope, and costs of an audit, e.g., task automation (Eulerich et al., 2022a) or remote audit (Teeter et al. 2010; Eulerich et al., 2022b). Our discussion of important variables influencing IT diffusion, i.e., the process by which the use of an IT spreads and grows, starts with the audit environment. These include technological development, data complexity, management support in IT adoption, the impact of regulators on the IAF, and cultural differences.

2.1 Environmental factors influencing IT diffusion

Prior research suggests that the size of the IAF is a good indicator of IT penetration. Team numbers alone say little about IT competence (Zhu & Kramer, 2005; Christ et al., 2021b). However, the size of an organization is positively associated with investment in digital solutions (Garven & Scarlet, 2020); therefore, higher levels of IT importance and IT knowledge are more likely in larger firms (Anderson et al., 2012). TBATs are imperative for larger internal audit departments as they face a challenging environment, which is related to AIS complexity (Kim et al., 2009; Li et al., 2018). As the level of risk increases with a company's growth, internal auditors need powerful IT infrastructure and systems to handle big data (Bhimani & Willcocks, 2014). In doing so, they must be aware not only of the benefits but also of the threats of digitization to prevent fraud (Gray & Debreceny, 2014) and reduce the likelihood of misconduct by managers (Ege, 2015). For example, continuous real-time monitoring techniques are used to detect anomalies (Vasarhelyi et al., 2012), as advances in technology make it easier to commit fraud (e.g., Dzuranin &

Mălăescu, 2015; Schneider et al., 2015). Moreover, by applying process mining, internal auditors can examine all transactions to determine whether managers made inappropriate expenditures (Jans et al., 2014). Traditional audit tools, in turn, do not appear to have the potential to provide sufficient assurance, underscoring the importance of new IT, which is increasing with firm size (Tang et al., 2017).

A consistent data environment is a precondition for successful IT use (Chen et al., 2012; Moffit & Vasarhelyi, 2013), and chief audit executives (CAEs) are decisive in this regard (Li et al., 2018). By having a say in setting the corporate's IT strategy, they significantly influence data quality in their firms (Dzuranin & Mălăescu, 2015). In addition, experienced CAEs secure financial resources (Anderson et al., 2012), resulting in higher budgets for the IAF (Garven & Scarlata, 2020). Practitioners should benefit from better infrastructure, which includes novel TBATs and IT training opportunities (Gonzalez et al., 2012; Tang et al., 2017). Such facilitating conditions can accelerate IT diffusion because specific skills are required to perform tests, e.g., defining input files and deriving complex commands (Braun & Davis, 2003). However, advanced IT has not been widely adopted because CAEs still struggle to quantify its cost-benefit ratio (Eulerich et al., 2023). Therefore, building positive relationships with internal audit stakeholders is critical (Lenz & Hahn, 2015). It helps to understand managers' needs and identify the most appropriate tools for day-to-day operations (Trotman & Duncan, 2018). This provides essential guidance, as professional associations encourage using innovative aids without stating a specification (IIA, 2017a, sec. 1220.A2). Regulatory advice could simplify the introduction of novel IT (Li et al., 2018), but due to a lack of normative requirements, many organizations do not know which tasks are worth automating (Eulerich et al., 2022a).

Furthermore, internal auditing is also influenced by the culture of the geographical region in which it operates (Christ et al., 2021b). For example, the US culture is characterized by low uncertainty avoidance, whereas the German cultural environment is associated with high uncertainty avoidance, i.e., Germans have a strong need to determine their own future and tend to avoid risks (Hofstede, 2001). Consequently, although the IAF is described as a global profession with uniform standards (Eulerich & Ratzinger-Sakel, 2018), cultural characteristics could have an impact on the use of new technologies (Gonzalez et al., 2012). In addition to such environmental-specific influences, person- and task-specific factors may impact IT diffusion.

2.2 Person- and task-specific factors influencing IT diffusion

Information systems literature suggests that the users themselves are a key factor in adopting novel tools. According to the technology acceptance model, awareness of one's self-efficacy (IT skills) increases the perception of the usability of an aid and the assessed usefulness of that system, which in turn affects behavioral intentions (Davis, 1989). In an audit context, perceived ease of use has a more significant impact on acceptance of advanced digital solutions, whereas perceived usefulness is more important regarding basic electronic tools (Kim et al., 2009). However, by conducting IT audits, internal auditors develop deep knowledge of the company's data structure to tailor their toolkit to its specifics (Li et al., 2018). Nevertheless, the deployment of audit technology falls short of expectations (Eulerich, 2023; Protiviti, 2023) and is partly done on an ad-hoc basis (Li et al., 2018). For example, most professionals perceive audit software as a tool for spot detection of fraud rather than a foundation to support daily work (Debreceny et al., 2005). A typical internal auditor with an accountancy background may not possess adequate skills to download data from the host system, which is stored in various forms and must be converted into an understandable computer language (Mahzan & Lymer, 2008). They accept basic technological features but not the advanced techniques (such as statistical analysis) associated with the need for in-depth knowledge (Kim et al., 2009). Thus, implementing new TBATs requires internal auditors to overcome a learning curve to become proficient with these automated tools (Gonzalez et al., 2012).

The tendency to leverage IT is affected by demographic characteristics (Venkatesh et al., 2003). They are likely to have a relatively rapid, short-term impact on technology diffusion, while others do so more slowly, taking years for effects to subside (George & Jones, 2000; Mitchell & James, 2001). This is critical because empirical results could be biased if researchers inadvertently or for simplistic reasons disregard the time perspective (Feliciano & Quick, 2022). Future time perspective refers to the extent to which a subject evaluates prospective events (Strathman et al., 1994; Zimbardo & Boyd, 1999). It includes three crucial relative stable cognitive dimensions: Future orientation, continuity, and affectivity (Kooij et al., 2018). High future orientation means an individual's focus on future events (Gjesme, 1979), whereas high continuity captures a person's belief that present actions influence future outcomes (Husman & Lens, 1999). Finally, high affectivity involves placing greater value on goals to be achieved in the future (de Volder & Lens, 1982), also known as delay of gratification (Mischel, 1961; Gjesme, 1979). By adopting the perspective of time, this study focuses on prospective IT importance (= future orientation) and current IT knowledge, considering long-term efforts (= continuity) to close identified IT gaps (= affectivity). We believe it will take at least three to five years (Omoteso et al., 2010; Eulerich et al., 2023) to realize the benefits of implementing TBATs, as it may be challenging to prepare practitioners with the appropriate skill set (Hass et al., 2006). Internal auditors tend to be less familiar with newer, emerging IT systems than with older, mature technologies already in regular use. Moreover, gender may serve as a key to understanding supervisor pressure, as IT adoption is initiated by the head of internal audit (Mahzan & Lymer, 2008/2014; Vasarhelyi et al., 2012). While social influence does not appear to have a significant impact on men's adoption decisions, as they instead rely on productivity factors, women are strongly motivated by the opinions of influential people who believe that a system should be used (Venkatesh & Morris, 2000). This implies different worker responses to technology implementation and the need for individual adoption strategies.

However, since the use of digital solutions depends on the activity types performed (Hass et al., 2006; Lenz & Hahn, 2015), not every novel technology is necessarily highly relevant and must be mastered at the expert level. For example, professionals who conduct audits in financial services may never been exposed to inventory observations, which significantly reduces the potential of drones (Feliciano & Quick, 2022). Therefore, high/low IT importance and IT knowledge levels should be considered relatively. Nevertheless, IT gaps express a lack of competence fit and must be treated as a priority. It is essential to identify the drivers of internal auditors' willingness in order to close the IT gap between relevance and knowledge.

3. Research Method

3.1 Questionnaire development

A major challenge in analyzing IT is determining the range of tools that can be considered new and emerging. Thus, if the scope of such an analysis becomes too large, we would lose the focus on relevant IT solutions. Conversely, a much narrower view would lead to an incomplete research subject. Therefore, we must clarify what should be subsumed under audit technologies. First, TBATs are those aids that enhance a professional's ability to perform a task (Eulerich et al., 2023). Accordingly, internal audit standards defines TBATs as "any automated audit tool" (IIA, 2017a, p. 24). This includes word processing, electronic working papers, spreadsheet applications (Braun & Davis, 2003), or generalized audit software (Debreceny et al., 2005; Mahzan & Lymer, 2014). However, advanced IT offers different opportunities than these rather conventional solutions. For example, population tests driven by sophisticated techniques may increase efficiency (Emett et al., 2023c) as they allow massive data collection in less time (Jans et al., 2014). Also, not surprisingly, various stakeholders believe predictive modeling to be of higher value because using a whole data set is more effective than sampling methods (Ballou et al., 2021). In addition, data visualization has improved in the form of easy-to-understand dashboards (Dilla et al., 2010, Baaske et al., 2023), while the inclusion of virtual avatars simplifies internal controls (Pickard et al., 2020). With all these inventions sparking interest in deeper exploration, our study will focus on this new generation of TBATs.

We drew on current research findings to identify innovative technologies that offer these and other benefits. Thereby, publications related to external auditing were considered. Although the functional role of public accountants differs, the work performed is comparable (IIA, 2017b).[2] Since the basic principles are the same (e.g., gathering data, seeking for errors/misstatements, analyzing the effectiveness of internal controls, and assessing various risks), the future toolkit of both professions could be mostly identical. Therefore, we started our literature review with 18 innovations recently evaluated by external auditors (Feliciano & Quick, 2021; Feliciano & Quick, 2022). An additional database search was conducted to verify the completeness of that list. We combined an iterative forward and backward approach (Webster & Watson, 2002) with the citation pearl-growing method (Rowley & Slack, 2004). By evaluating titles, abstracts, and keywords in electronic libraries[3], we specified our search whenever we found relevant (new) aspects. As a result, the number of IT to be investigated was initially expanded.

Since businesses continuously invest in technology (Protiviti, 2023), we revised our list based on practitioner feedback. Three selection criteria drove inclusion (or exclusion): The overall maturity of a digital innovation, its functional utility for internal auditing, and its potential for penetration within the next five years. After consulting with eight internal audit experts, most of them with leadership experience in larger organizations, it became clear that the proposed additions offered limited value. Consequently, these suggestions

2 Nevertheless, there are significant differences between internal auditing/auditors and external auditing/auditors, e.g., regarding education, the audit scope (much broader in internal auditing), or the time reference (internal auditing is more forward-looking and continuous).

3 Among others: EBSCO Host, Google Scholar, and SSRN. In addition to high-quality outlets (considering journals rated 4 and 4* in the ABS Journal Guide; also leading journals in AIS such as Emerging Technologies in Accounting, International Journal of Accounting Information Systems, or Journal of Information Systems), we have also focused on dissertations and working papers.

were discarded (e.g., 3D printing[4], internet of things[5]), while the adapted framework from external audit remained unchanged. In the final version, we added collaboration platforms because they greatly facilitate interaction in virtual teams (Bauer et al., 2022). This resulted in 19 key technologies. See Table 1.

Technology (briefly defined)	Reference (exemplary)
Augmented reality via smart glasses that underlay live images with background knowledge, e.g., for on-site inventories	Carmigniani et al., 2011
Blockchain technology based on smart contracts, e.g., for rules-based tracking of internal audit requirements	Schmitz & Leoni, 2019
Chatbots as text input-based dialog systems, e.g., for accessing corporate standards, wiki content and FAQ answers	Adamopoulou & Moussiades, 2020
Cloud computing for continuous monitoring of data and applications, e.g., for checking IT authorizations during the year	Lins et al., 2018
Collaboration platforms as a networking base that centralize group work (task assignment, documentation, file storage, etc.)	Bauer et al., 2022
Data mining to uncover unknown patterns in test material, e.g., anomalies in disbursement processes ("unsupervised learning")	Gray & Debreceny, 2014
Drone utilization, e.g., for remote inventory with integrated barcode scanner or controllable RFID capture	Appelbaum & Nehmer, 2017
In-memory databases for rapid retrieval of large data from the working memory, e.g., via HANA in data warehouses (or data lakes)	Chen et al., 2012
Learning nuggets to quickly impart "how-to" knowledge through short audio sequences or video recordings	Bailey et al., 2006
Machine learning to search for known patterns via trained algorithms, e.g., for the accrual of an accounting period ("supervised learning")	Ding et al., 2020
Natural language generation for automatic text creation in real time, e.g., for translation of foreign language content (“writing”)	Kokina & Davenport, 2017
Natural language understanding as digitized text analysis, e.g., for checking two-signature control (“reading”)	Burns & Igou, 2019
Online meeting solutions for remote communication with audio or video telephony, instant messaging, and screen sharing	Teeter et al., 2010
Predictive analytics for statistical multivariate forecasting, e.g., as part of audit planning and risk assessment of core processes	Kuenkaikaew, 2013

4 3D printing is synonymous with additive manufacturing, which means the production of an object by depositing material layer by layer from a computer-aided design model (Shahrubudin et al., 2019). According to an interviewee, it has been predominantly used in agriculture, automotive, aviation, locomotive, and healthcare “… but not in service industry (= internal audit)”.

5 Following Atzori et al. (2010), the internet of things (IoT) refers to the interconnection of electronic devices (= things) based on embedded sensors that exchange data over a wireless network without human intervention (= internet). Although internal auditors could use IoT to analyze real-time information, interviewees saw it as "a new area of audit risk rather than a practical tool".

Technology (briefly defined)	Reference (exemplary)
Process mining for the identification, visualization and analysis of data flows and business processes via flow charts	Jans & Hosseinpour, 2019
Robotic process automation of repetitive tasks, e.g., the reading and consolidation of data from various IT systems	Eulerich et al., 2022a
Scanbots for converting hardcopies into editable file formats (i.e., PDF), e.g., in the run-up to a contract clause audit	Mithe et al., 2013
Self-service reports for user-friendly data displays through easy-to-use intuitive dashboards with drill-down functionality	Dilla et al., 2010
Virtual reality (VR) via VR-Ocolus, e.g., for avatar-based interaction in digitally generated 3D meeting rooms	LaValle, 2023

Table 1: Surveyed disruptive technologies (in alphabetic order)

To address our first research question, we asked respondents how they assessed the future relevance of the specific technology within the next five years on a 7-point Likert scale (from 1 = not important at all to 7 = very important). For those who did not feel able to give an appropriate answer, the category "I do not know" could be chosen alternatively. Afterwards, the participants were asked to rate their current technical skills for the same 19 TBATs, again on a 7-point Likert scale (from 1 = no knowledge to 7 = expert knowledge), to collect data to analyze our second and third research questions. The instrument was supplemented with various demographic questions to explore our fourth research question. We administered the study online using SoSci Survey. The recommendations of Podsakoff et al. (2003) were considered to avoid common method bias. For example, we resorted the order of items (= technologies) in transitioning from IT importance to IT knowledge as subjects progressed through the questionnaire. Also, our study design was pre-tested with two accounting academics who served as a proxy for internal audit professionals. The comments we received related to the wording used, which we considered when drafting the final version. The extracted IT list could be biased as our interviewees referred to innovations adopted in their organizations. However, the risk of such bias is limited since we were dealing with experts from larger companies, who often act as technological first movers (Lieberman & Montgomery, 1988).

3.2 Questionnaire distribution

We focus on the German-speaking area, i.e., Germany, Austria, and Switzerland, where similar perceptions towards moderate regulation exist (Eulerich, 2023). We applied a two-stage survey procedure. First, initial responses were solicited via LinkedIn. By posting a call for study participation that included a link to the questionnaire, 36 returns from internal auditors were received by the end of 2022. We cannot state a response rate because it is unknown how many subjects noticed the information about our research project. Second, we identified potential participants via the website of the German Institute of Internal Auditing (IIA) and a conference of the German IIA, where some of the members are listed with contact details. Email addresses of these individuals were manually collected and complemented with further internal auditors we found through a social media search.[6] Applying the email logic of the company for which an internal auditor works, a database of nearly 1,000 contacts was compiled. Survey distribution commenced in April 2023, consisted of two waves (= one email reminder), and ended in June 2023. As a result, another 129 internal auditors responded.[7] The return rate of this subsample (= 12.9 %) is higher than that of most previous research on internal audit technology (e.g., Mahzan & Lymer, 2008 with 7.9 %; Kim et al., 2009 with 11.6 %; Li et al., 2018 with 9.0 %).[8]

The initial sample consisted of 165 respondents from German-speaking countries. Before the in-depth analyses, we deleted data from one subject due to straightlining patterns, i.e., identical answers to a series of statements, in conjunction with a short processing time, indicating poor response quality (Zhang & Conrad, 2014; Schonlau & Toepoel, 2015). Also, one participant reported being employed outside our three target countries. This observation was removed as well. Next, twenty responses with missing values that exceeded 15 % of the questions were excluded (Hair et al., 2019). For those cases below this threshold (= 17), we calculated the missing values by applying the expectation-maximization algorithm (Little's MCAR-Test: p= 0.804, with missing values by item below 5.0 % and completely at random). In the end, 143 usable observations remained. Paired t-tests were conducted to test for nonresponse bias (Sax et al., 2003).[9] We found no significant differences within our sample, indicating that there is no nonresponse bias.[10]

4. Empirical results

4.1 Participants' characteristics

Table 2 summarizes the demographic statistics. Most participants are male (77.5 %), employed in Germany (94.4 %), and hold a master's degree (66.4 %). Average professional experience in auditing (internal and external) is high (14.4 years), with 58.7 % of respondents reporting being older than 45. The majority (52.4 %) has relevant certificates, such as Certified Internal Auditor (CIA), Certified Government Auditing Professional (CGAP), and a Certification in Control Self Assessment (CCSA). Regarding position titles, CAEs (36.4 %) and audit team leaders (34.2 %) comprise a large proportion of the sample. We, therefore, assume that IT-enabled decision-making should be widespread among subjects (Anderson et al., 2012). Conversely, less than half of our internal auditors (43.7 %) indicated belonging to the financial industry, in which certain digital solutions may not be deployed, e.g., drones (Appelbaum & Nehmer, 2017; Christ et al., 2021a). Given that

6 Because internal auditors are hard to reach for research purposes, our data collection should not be limited to CIAs and individuals with similar certificates.

7 We performed t-tests to analyze whether the two ways of acquiring participants matter. However, we did not find significant differences regarding future relevance and current knowledge related to the 19 examined technologies.

8 Further, eight internal auditors refused to participate for lack of time or other reasons. Moreover, it remains unclear whether all those contacted received our invitation due to spam filters. 141 email addresses were invalid. In these cases, our request never arrived. Therefore, the effective return rate is higher. Based on valid email addresses, the response rate is even 15.0 %.

9 We divided the final sample into two subsets: Those who finished earlier than the median completion time and those who finished later than the median completion time (Li et al., 2018). Alternatively, responses were split by the presence of certificates (yes/no), as it may be that subjects without additional qualifications have different views (Anderson et al., 2012; Tang et al., 2017).

10 The twofold comparison of the toolkit resulted in 76 paired t-tests, of which six items had statistically significant response differences (p< 0.05, two-tailed). Thus, the nonresponse bias for this survey can be considered mild.

85.8 % of respondents stated working for a large company, where the adoption of innovative technology is more likely (Zhu & Kramer, 2005), we expect to receive meaningful answers in the further course.

Gender*	N	%		Country	N	%
Male	110	77.5		Germany	135	94.4
Female	32	22.5		Austria/Switzerland	8	5.6
Education	N	%		Position	N	%
No undergraduation	8	5.6		Junior auditor	10	7.0
Bachelor degree	29	20.3		Senior auditor	32	22.4
Master degree	95	66.4		Audit team leader	49	34.2
Doctoral degree	11	7.7		Chief audit executive	52	36.4
Certificates	N	%		Financial industry*	N	%
Yes	75	52.4		Yes	62	43.7
No	68	47.6		No	80	56.3
Age	N	%		Firm size*	N	%
Below 36 years	20	14.0		Small/Medium	20	14.2
From 36 to 45 years	39	27.3		Large	121	85.8
From 46 to 55 years	51	35.7		Experience (YRS)	Min	Max
Above 55 years	33	23.0		N = 143; $\overline{x}$ = 14.4	1	43

Table 2: Participant's characteristics (Total sample = 143)[11]

4.2 IT importance, IT knowledge, and IT gap

We calculated means for all items to get an overall measure of participants' assessments of relevance and knowledge. In the first step, we analyzed IT importance and IT knowledge separately and then in comparison (Ismail & Abidin, 2009).[12] Starting with IT importance, Table 3 presents the results in descending order. Corresponding standard deviations (SD) and t-values (t) are also given.

As shown, the self-perceived relevance of TBATs ranges on average from 2.681 to 6.490. Fifteen digital solutions exceeded the scale midpoint of 4.000, meaning that subjects rated their importance relatively high. Online meeting solutions rank first, data mining second, and cloud computing third, followed by collaboration platforms. At the bottom of the IT list, blockchain technology, augmented reality, drone utilization, and virtual reality remain below this threshold, implying relative unimportance. Overall, the total mean value is 4.705.

11 For gender, financial industry, and firm size, N is smaller than 143, since the questionnaire was not completed in full by all subjects.

12 Although our scale is ordinal, t-tests were used because they are robust, especially as the sample size increases (Greenstein-Prosch et al., 2008).

Surveyed innovative technologies	IT importance (in 3 to 5 years)			
	Rank	Mean	SD	t
Online meeting solutions	1	6.490***	.903	32.976
Data mining	2	5.850***	1.193	18.548
Cloud computing	3	5.773***	1.407	15.066
Collaboration platforms	4	5.669***	1.424	14.012
Process mining	5	5.578***	1.421	13.279
Self-service reports	6	5.418***	1.345	12.610
Robotic process automation	7	5.196***	1.435	9.972
In-memory databases	8	4.972***	1.568	7.416
Machine learning	9	4.957***	1.491	7.673
Natural language generation	10	4.761***	1.626	5.598
Scanbots	11	4.706***	1.639	5.152
Predictive analytics	12	4.686***	1.543	5.313
Natural language understanding	13	4.619***	1.536	4.815
Learning nuggets	14	4.395***	1.640	2.881
Chatbots	15	4.236*	1.687	1.675
Blockchain technology	16	3.656**	1.679	-2.450
Augmented reality	17	2.951***	1.474	-8.508
Drone utilization	18	2.794***	1.610	-8.962
Virtual reality	19	2.681***	1.507	-10.464
TOTAL (IT importance)	---	4.705***	.778	10.832

Table 3: Technology ranking according to IT importance[13]

Conducting one-sample t-tests, we checked whether the means of the 19 TBATs significantly deviate from the midpoint of the Likert scale (= 4.000) because exceeding (or falling below) this midpoint is equivalent to classifying an innovative IT as relatively (un)important). All means significantly differ from the midpoint (mostly $p< 0.01$, two-tailed). Fifteen technologies are perceived as important, and four technologies as unimportant.

The high importance scores for various IT applications support the idea that internal auditors cover various tasks (Anderson et al., 2012). Therefore, different aids become relevant simultaneously (Tang et al., 2017; Li et al., 2018). In addition, the few low mean values indicate little functional redundancy among the selected TBATs.[14] When two (or more) digital solutions serve a similar purpose, the benefits of one tool are not "realized"

13 One-sample t-test, two tailed, test value: Mean of 4.000. Significance levels: *** $p< 0.01$; ** $p< 0.05$; * $p< 0.10$.

14 According to Moore et al. (2021), (very) low coefficients ($r<.500$) were found for about 95 % of all bivariate correlations, suggesting sufficient discrimination among the TBATs assessed.

until it leads to the elimination of the alternative(s) (Fischer, 1996). For example, it is unlikely that "competing" communication technologies will prevail simultaneously with equal relevance (see online meeting solutions with the best mean and virtual reality with the worst mean). Further, internal auditors should develop preferences for certain tools depending on the tasks they are responsible for. Thus, the low perceived usefulness of innovative technologies could also explain their lowly assessed importance (Kim et al., 2009).

Surveyed innovative technologies	IT knowledge (currently)			
	Rank	Mean	SD	t
Online meeting solutions	1	6.189***	1.304	25.307
Collaboration platforms	2	5.070***	1.714	7.464
Cloud computing	3	4.552***	1.727	3.826
Process mining	4	4.245*	1.700	1.722
Self-service reports	5	3.972	1.784	-.188
Data mining	6	3.930	1.706	-.490
Robotic process automation	7	3.517***	1.727	-3.340
Learning nuggets	8	3.503***	1.883	-3.152
Scanbots	9	3.168***	1.712	-5.814
In-memory databases	10	3.119***	1.726	-6.105
Chatbots	11	2.951***	1.450	-8.649
Predictive analytics	12	2.909***	1.703	-7.660
Natural language generation	13	2.895***	1.617	-8.170
Machine learning	14	2.860***	1.698	-8.030
Natural language understanding	15	2.601***	1.530	-10.933
Blockchain technology	16	2.371***	1.427	-13.649
Virtual reality	17	1.888***	1.245	-20.280
Augmented reality	18	1.846***	1.153	-22.348
Drone utilization	19	1.734***	1.210	-22.392
TOTAL (IT knowledge)	---	3.333***	1.011	-7.889

Table 4: Technology ranking according to IT knowledge[15]

Regarding IT knowledge, the analysis revealed significantly lower values (from 1.734 to 6.189). Only four TBATs exceed the midpoint of 4.000 (= relatively knowledgeable). These include online meeting solutions, collaboration platforms, cloud computing, and process mining. In contrast, 15 applications fall below this threshold, with blockchain technology,

15 One-sample t-test, two tailed, test value: Mean of 4.000. Significance levels: *** $p< 0.01$; ** $p< 0.05$; * $p< 0.10$.

virtual reality, augmented reality, and drone utilization at the lower end of the ranking. Again, we performed one-sample t-tests to investigate whether the means of the 19 items significantly differ from the midpoint. Except for two technologies (= self-service reports and data mining), all tools are significant at the p-level of 0.01 (two-tailed) (see Table 4).

The relatively poor level of IT knowledge (total mean: 3.333) is not surprising. Since perceived ease of use is a strong behavioral determinant of advanced IT (Kim et al., 2009) and represents effort expectancy (Gonzalez et al., 2012), our results suggest that some technologies may be more challenging to apply. For example, extracting needed information from a massive database can only be solved with complex techniques (Li et al., 2018), making it challenging to build expertise. In contrast, the high value for online meeting solutions is within expectation given the disruptive remote practice post-COVID-19 (Bauer et al., 2022; Eulerich et al., 2022b). In addition, novel aids have inherently limited diffusion, which means that the number of experts is likely to be limited to a small group of people. For example, the below-average scores for immersive technologies (= augmented and virtual reality) indicate that these innovations are still emerging. In addition, the low skills in the use of drones could be related to the legal framework, which is more restrictive in Germany than elsewhere (Appelbaum & Nehmer, 2017; Christ et al., 2021a).

Next, a deviation analysis was performed to determine the degree of alignment between relevance and knowledge (Ismail & Abidin, 2009). For each of the 19 TBATs, we computed the mean delta by summing the absolute difference for all responses and dividing it by the number of total subjects. A large divergence would suggest a critical status (Venkatraman, 1989). The corresponding results are depicted in Figure 1. The gray bars in the left part of the diagram present the absolute lack of fit comparing IT importance and IT knowledge. In addition, the relative lack of fit is illustrated as a separate bar on the right-hand side.

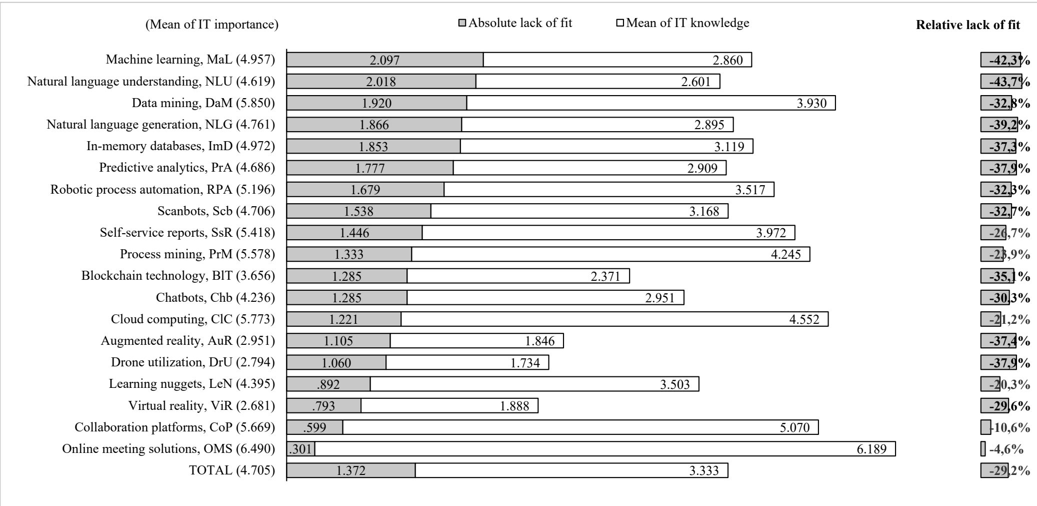

Figure 1: Lack of fit between IT knowledge and IT importance regarding means[16]

16 Note: One-sample t-test, two tailed, test value: Mean of 0.000. All means are significant at p< 0.01. Related t-values of absolute lack of fit: MaL 12.951; NLU 12.623; DaM 11.748; NLG 12.427; ImD 10.955; PrA 11.382; RPA 9.791; Scb 9.014; SsR 9.442; PrM 8.079; BlT 8.282; Chb 7.409; ClC 8.018; AuR 8.893; DrU 6.976; LeN 5.597; ViR 5.717; CoP 4.407; OMS 3.176; TOTAL 14.477.

Looking at technologies that are relatively relevant (IT importance > 4.000), small deviations were found in six applications, which have a relative IT gap of less than -29.2 % (= average total value). These include online meeting solutions and collaboration platforms, learning nuggets, cloud computing, process mining, and self-service reports (see the scores in blue). We consider them comparatively easy to use. Vice versa, the alignment of the remaining (important) tools is low, with the absolute lack of fit reaching a maximum of 2.097 (total average score: 1.372). Machine learning, natural language understanding, data mining, and natural language generation are conceptually too abstract or challenging to handle, to name only those with a large mismatch. We tested whether the absolute lack of fit substantially differs from "0.000". One-sample t-tests were conducted for analyzing the IT gap of all 19 technologies by applying a test value of 0.000 as a perfect match. Our results indicated a significant delta for all TBATs examined ($p< 0.01$, two-tailed).

One reason for these multiple IT gaps may lie in different time perspectives that we used to get more comprehensive results (George & Jones, 2000; Mitchell & James, 2001). While the mean scores for IT importance are based on a prospective view, the responses on IT knowledge relate to the current state of knowledge. As soon as the mean of knowledge reaches the level of relevance, there would be an ideal match between efficient task completion (= IT knowledge) and effective task orientation (= IT importance). However, if the former value exceeds the latter, this may indicate that a digital innovation has probably passed its peak, as the functional benefit may be lower compared to other emerging alternatives. Ergo, a tool might be no longer indispensable and could be replaced in three to five years.[17]

4.3 Impact of participant's characteristics

Since the personal context of our subjects differs, the question arises as to which individual factors significantly impact IT importance, IT knowledge, and IT gap. Building technical skills to apply TBATs can be lengthy (Feliciano & Quick, 2022), so understanding similarities and differences across all three dimensions is of deeper interest. Because data on several demographic variables were collected, we used these responses to examine the association between respondents' characteristics and their perceptions of innovative technology. To this end, we ran three logistic regressions in which the proxy was either (1) $ITimp_{di}$ (IT importance), (2) $ITkno_{di}$ (IT knowledge), or (3) $ITgap_{di}$ (IT gap), considering digital solution d and internal auditor i. This led to the following models:[18]

(1) $ITimp_{di} = β0 + β1SEX_{di} + β2AGE_{di} + β3YRS_{di} + ß4EDU_{di} + β5POS_{di} + ß6FIN_{di}$;
(2) $ITkno_{di} = β0 + β1SEX_{di} + β2AGE_{di} + β3YRS_{di} + ß4EDU_{di} + β5POS_{di} + ß6FIN_{di}$;
(3) $ITgap_{di} = β0 + β1SEX_{di} + β2AGE_{di} + β3YRS_{di} + ß4EDU_{di} + β5POS_{di} + ß6FIN_{di}$.

Similar to prior literature, we include gender (SEX), age (AGE), and (career) experience (YRS) as potential moderators (Venkatesh et al., 2003). Thereby, SEX_{di} equals „1" for

17 However, such a scenario will only occur if the importance of IT decreases. Otherwise, the dispensing with a tool about which sufficient knowledge is available would not be justified.

18 Since the sample proportion of participants from small and medium-sized companies is minimal, we dropped firm size from the regression models due to its low statistical power. The same applies to the breakdown of subjects by country, with only a minority of non-German origin. In addition, we excluded certificates from the in-depth analysis, as the non-response bias test did not reveal any differences between respondents. When including this variable to the regressions, their power is lower and "certificate" is insignificant.

male subjects, while „2“ represents women; AGE_{di} equals „1“ for respondents who are below 36 years, „2“ for respondents who are between 36–45 years, and „3“ for respondents who are between 46–55 years, while „4“ represents participants who are above 55 years; finally, YRS_{di} equals the number of years of career experience in auditing (internal and external). In addition, since our study focuses on practitioners with academic background in larger companies, we tested for education (EDU) and position title (POS). Here, EDU_{di} equals „1“ for respondents without an academic degree, „2“ for respondents with a bachelor's degree, and „3“ for respondents with a master's degree, while „4“ represents participants with a doctorate or higher; furthermore, POS_{di} equals „1“ for junior auditors, „2“ for senior auditors, and „3“ for audit team leaders, while „4“ represents CAEs. Finally, we suspect that adopting relevant tools might vary by industry. For example, multinational banks (Jans et al., 2014) and insurance companies (Ding et al., 2020) must carry out complex transactions daily, implying the need for advanced techniques, but not all technology can add value in the service sector (Appelbaum & Nehmer, 2017; Christ et al., 2021a). This makes the use of digital aids selective. Therefore, we also chose the financial industry as a moderator. FIN_{di} equals „1“ for respondents who are working in financial services and, „2“ otherwise.

We tested the regression models for multicollinearity by calculating variance inflation factors (VIF). VIF values above 4.000 indicate a high correlation and cause a multicollinearity concern (Hair et al., 2019). However, for our regressions, the VIF ranges from 1.043 to 1.705 and thus are unproblematic.

Regression results are depicted in Table 5. Regarding IT importance, career experience yielded a significantly positive effect at $p< 0.01$, while age has a significantly negative impact (p-level < 0.10). The influence of the former (β=.279) is stronger than the latter's (β= -.194). Experienced employees may find several ways for professional help throughout the organization (Venkatesh et al., 2003), e.g., more knowledgeable peers, which may result in a higher perceived relevance of TBATs (Mahzan & Lymer, 2008/2014; Li et al., 2018). Vice versa, younger people seem more adaptive to new inventions than older individuals because of their inquisitiveness, creativity, and IT use habits (Morris & Venkatesh, 2000). For this reason, IT importance could decrease with age. Also, as a third demographic factor, the financial industry has a significantly positive impact on the perceptions of technological relevance ($p< 0.05$; β=.188). We found lower significant mean values (at $p< 0.10$) among participants of this sector (untabulated: 4.572) compared to the scores of other respondents (untabulated: 4.807). This implies that some innovations have little or no impact on this industry. Untabulated t-tests revealed significant differences for three electronic solutions: Augmented reality and drone utilization (both at $p< 0.01$, two-tailed), as well as scanbots ($p< 0.10$, two-tailed). For these aids, the disruptive potential within financial services seems limited in the coming years.

Independent variables	Dependent variables		
	IT importance ($ITimp_{di}$)	IT knowledge ($ITkno_{di}$)	IT gap ($ITgap_{di}$)
Gender (SEX_{di})	.105 (.158)	-.205** (.207)	.256*** (.229)
Age (AGE_{di})	-.194* (.086)	.017 (.112)	-.148 (.124)
Experience (YRS_{di})	.279*** (.010)	.100 (.013)	.102 (.015)
Education (EDU_{di})	-.026 (.078)	.104 (.102)	-.111 (.113)
Position title (POS_{di})	-.094 (.079)	-.137 (.103)	.058 (.114)
Financial industry (FIN_{di})	.188** (.134)	.122 (.175)	.020 (.193)
Observations	143	143	143
Adjusted R^2	0.048	0.043	0.062
F statistic (df = 6; 134)	2.180**	2.041*	2.550**

Table 5: Impact of auditor characteristics on IT importance, IT knowledge, and IT gap[19]

In the analysis of IT knowledge and IT gap, gender is significant in both regression models with $p< 0.05$ (β= -.205) and $p< 0.01$ (β=.256), respectively.[20] On the one hand, female participants' technical skills are comparatively low (not tabulated: 2.952; male peers: 3.443), indicating some anxiety in using new tools (Venkatesh & Morris, 2000). On the other hand, the deltas between relevance and knowledge are relatively large, although females perceive IT as more important (not tabulated: 4.869; male peers: 4.650); however, this effect is not significant. Therefore, the technological gap remains stable. One possible reason could be that CAEs demand and encourage the use of emerging tools (Mahzan & Lymer, 2008/2014; Vasarhelyi et al., 2012; Li et al., 2018), to which less skillful women might be initially more receptive. As they gain experience with technology, the influence of

19 Significance levels: *** p< 0.01; ** p< 0.05; * p< 0.10. We report standardized coefficients, with standard errors in parentheses. Unstandardized intercept terms are as follows: IT importance 4.516 (.491)***; IT knowledge 3.298 (.642)***; IT gap 1.217 (.711)*. Gender equals „1“ for male subjects, while „2“ represents women. Age equals „1“ for respondents who are below 36 years, „2“ for respondents who are between 36–45 years, and „3“ for respondents who are between 46–55 years, while „4“ represents participants who are above 55 years. Experience equals the number of years of professional work in auditing (internal and external). Education equals „1“ for respondents without an academic degree, „2“ for respondents with a bachelor's degree, and „3“ for respondents with a master's degree, while „4“ represents participants with a doctorate or higher. Position equals „1“ for junior auditors, „2“ for senior auditors, and „3“ for audit team leaders, while „4“ represents CAEs. Finally, financial industry equals "1" for respondents who are working in financial services and "2" otherwise.

20 Qazi et al. (2022) provide a literature review on gender differences in information and communication technology use and skills.

more knowledgeable individuals is expected to diminish, with individuals relying more on their assessments to shape their perceptions of IT rather than the opinions of supervisors (or peers) (Venkatesh & Morris, 2000). Interestingly, similar findings are also evident in public accounting firms (Feliciano & Quick, 2022), according to which a gender gap affects the entire audit domain. Overall, no complementary effects were found regarding experience, age, academic education, position title, and financial industry.

5. Conclusions and limitations

This paper presents the results of our research project with internal auditors from the three countries of the DACH region. We analyzed different types of IT that potentially affect the internal audit profession and posed four research questions. First, the study examined which TBATs will be relevant in three to five years (IT importance). Fifteen of 19 technologies are ranked as important by 143 respondents. Online meeting solutions top the list, followed by data mining, cloud computing, and collaboration platforms. Conversely, we identified four applications that participants rated as relatively meaningless. Virtual reality received the lowest score of all innovations surveyed. Second, our study focused on the current state of technical knowledge among internal auditors regarding novel IT (IT knowledge). Overall, subjects assessed themselves as knowledgeable in four tools: Online meeting solutions, collaboration platforms, cloud computing, and process mining. These are user-friendly digital solutions with high penetration in organizations. Vice versa, the other TBATs could be perceived as too complex, which makes skill acquisition difficult. Third, this paper addresses a mismatch between future relevance and current knowledge for modern technologies in internal auditing (IT gap). When comparing the mean values, the items consistently received lower scores on IT knowledge than on IT importance, indicating a notable lack of convergence for the entire toolkit. Thus, substantial efforts will be needed in the coming years to bring technical literacy up to the level of practical importance. Fourth, we explored the influence of internal auditor demographics on all three variables, i.e., IT importance, IT knowledge, and IT gap (impact factors). Experienced practitioners rated a significantly higher future relevance of innovative technologies, as did younger professionals and those outside the financial industry. IT skills are significantly lower among women, while the IT gap is significantly smaller among men. We conclude that internal auditors have different starting positions in digital change.

To sum up, internal auditors face considerable challenges as the application of knowledge is essential for making informed decisions. The urgent need (Eulerich, 2023) and the limited opportunities to hire IT specialists (Christ et al., 2021b; Seidenstein et al., 2024), further highlight and exacerbate the lack of expertise. While task delegation has become routine in external auditing (Hux, 2017; Bauer & Estep, 2019), where shared service centers offer technical support (Salijeni et al., 2019; Aschauer & Quick, 2021), many internal audit departments are not large enough (Anderson et al., 2012) to recoup investments in such functions. Instead, holistic skill development remains the key to transforming IT capabilities. By increasing corporate training, updating educational standards, and revising academic programs, we emphasize the importance of collaboration within the industry (Jackson et al., 2022). Generally, post-implementation IT training providing basic knowledge to internal auditors (Vasarhelyhi et al., 2012; Tang et al., 2017) is critical in adopting digital innovations (Venkatesh et al., 2003). By revealing the most promising future TBATs, our paper can help CAEs prioritize their efforts effectively. Moreover, by identifying IT gaps, the study illustrates the smallest deltas between IT relevance and IT knowledge. Because some technologies may be easier to learn than others, such as data visualization techniques (Weirich et al., 2018; Higginbotham et al., 2021), we implicitly guide ongoing education. Current knowledge in online meeting solutions indicates that internal auditors could quickly improve their knowledge through application, as pre-pandemic levels were perceived to be low (Eulerich et al., 2022b). In addition, technical literacy should be addressed more intensively in continuing professional education (CPE). The IIA does offer various training courses, where techniques for effective testing, data analytics or data visualization, among others, are covered. However, the course content is based on conventional spreadsheet applications and should therefore be revised with a view to innovative IT. In this context, it would be conceivable to fix a minimum number of CPE points for participation in IT-related training courses to encourage the acquisition of IT knowledge based on the upcoming standards by the global IIA. In the same vein, universities have been criticized for not developing graduates with the skills required by employers (Chang & Hwang, 2003; Aldredge et al., 2021). Since our regression analysis did not confirm education as a significant factor, we suspect a gap between what (young) professionals need and what educators teach. Gone are the days when traditional accounting education was sufficient (Christ et al., 2021b), and „generalists“ had wide-ranging career opportunities (Kotb et al., 2014). As IT increasingly impacts business structures, academia must adapt its curricula accordingly (Qasim & Kharbat, 2020; Jackson et al., 2022). Considering the differences between men and women, university programs could be tailored to meet the needs of both groups. The recommendations are not new: IT instructors may wish to emphasize usefulness issues for males while offering females a more balanced analysis that includes productivity aspects, process reflection, and role model testimonials (Morris & Venkatesh, 2000). Regarding age, educators should also emphasize how new technology helps users achieve more effective results, as the most important factor for younger people is instrumentality (Venkatesh & Morris, 2000).

Our study has certain limitations. First, we measured subjects' self-perception of innovative IT, which likely differs from actual knowledge. Empirical research on TBATs indicates some overestimation by participants (Kennedy & Peecher, 1997). Therefore, the true level of IT knowledge might be even lower than that assessed by our participants. Second, despite a thorough literature review and several interviews conducted, other modern IT-based solutions may have been overlooked. Since we analyzed selected TBATs, the total mean value could not be representative. Given the rapidly changing and open-ended nature of digital aids (Greenstein-Prosch et al., 2008) and newly emerging technologies, like ChatGPT (e.g., Emett et al., 2023a; Wood et al., 2023; Eulerich & Wood, 2024), adding more innovations in subsequent analyses makes sense. This study provides a good starting point for further investigations of the internal auditor's toolkit. Third, the assumed future relevance of TBATs may vary over time. Therefore, we cannot guarantee whether the identified gaps will remain, and the need to narrow such gaps could become obsolete (Feliciano & Quick, 2022). If alternative solutions emerge disruptively, they could gain momentum in the short term and change opinions about useful tools. However, by using innovative technologies in internal auditing, firms might be able to alter the rules of competition. Based on such competitive pressure, companies are likely to adopt a technology when a competitor has done so before (Zhu & Kramer, 2005). However, our participants are mostly employed in larger organizations that adopt electronic aids early (Lieberman & Montgomery, 1988). Thus, the results on IT gap should be a good indicator. Fourth, various demographic data were collected, however, we could not use them fully for our regressions due to the sample distribution. In particular, the variables country and firm size are unbalanced. Further research may resolve this issue given sufficient observations related to other countries or smaller firms. In this regard, other explanatory factors, e.g., IT complexity (Kim et al., 2009; Li et al., 2018), should complement our research model to increase the proportion of explained variance. Moreover, it is possible that relevant tools may vary not only in financial services but also in other industries. A more granular analysis of industry impact could find related answers. Fifth, our regressions are characterized by a relatively low power, which could be caused by a small sample size and may indicate omitted variables. Thus, future research could analyze the impact of further demographic characteristics (e.g., ethnic background, IT experience, or willingness to change, respectively, intellectual agility). The small sample size also reduced the likelihood of significant results. Finally, we analyzed the responses of internal auditors from the DACH region, with a focus on Germany. Thus, the results may only be applicable to this geographic area (Eulerich & Ratzinger-Sakel, 2018). Nonetheless, IAF in Germany (Austria or Switzerland) is well developed (Eulerich, 2023) and could serve as an adequate benchmark for global comparison. Another promising avenue for future research would be investigating what degree of knowledge internal auditors must possess to use technologies meaningfully because application knowledge could be sufficient for specific technologies, e.g., collaboration platforms. In contrast, applying other technologies, e.g., machine learning (e.g., Bao et al., 2020; Bertomeu et al., 2021), may require user insights into machine learning technologies. Furthermore, future research could develop guidelines on how internal auditors could become familiar with new technologies applying design science research.

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