Editorial

Innovations in Auditing and Other Assurance Engagements

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Abstract: The field of auditing is undergoing a fundamental change due to disruptive technologies such as big data and artificial intelligence, which fundamentally transform the financial reporting process and, subsequently, the way financial statement audits are conducted. The editorial of this special issue focuses on three selected perspectives: audit data analytics, artificial intelligence in auditing, and sustainability report assurance. This special issue presents three papers: 1) to the role of conscientiousness on the effects of continuous auditing and COVID-19 on employees' likelihood of complying with the internal control system, 2) how internal auditors assess the importance of and their knowledge about innovative technologies, and 3) a categorization and classification method related to artificial intelligence technologies and the risk-based audit approach.

The external audit function is crucial to financial stability and a key contributor to trust and market confidence. The purpose of an audit is to enhance the credibility of financial reports prepared by management. This function can only be fulfilled if an adequate quality is provided. According to the generally accepted definition, audit quality is the market-assessed joint probability that a given auditor will discover a breach in the client's accounting system and report the breach. However, audit markets are characterized by excessive competition, which results in pressure on audit fees and may threaten audit quality due to the resulting need for reduced audit costs.

External and internal auditing are undergoing a fundamental digital transformation, mainly due to the use of disruptive technologies such as advanced data analytics and artificial intelligence, which will fundamentally change the financial reporting process and, thus, how external and internal auditors conduct audits. In addition, the subject matter of auditing is changing. A recent example is assurance on ESEF (European Single Reporting Format) reports.

Other innovations relate to new elements of business reporting, such as the preparation and assurance of sustainability reports – often also called ESG reports (Environment, Social, Governance). Since companies are steadily facing new regulatory requirements, demanding a transformation to more sustainability concerning their activities, sustainability information is becoming increasingly crucial for stakeholders (e.g., investors, banks, employees, or non-government organizations). Assurance on sustainability reports can increase their credibility. In many legal areas, such an assurance can be conducted by accountants or other independent assurance service providers.

Below, we describe three selected research perspectives from the fields of digital transformation and sustainability assurance in more detail:

Audit Data Analytics

Innovative technology often refers to Audit Data Analytics (ADA). Data analytics is a broad term, often defined as "the science and art of discovering and analyzing patterns, deviations and inconsistencies, and extracting other useful information in the data underlying or related to the subject matter of an audit through analysis, modeling, and visualization for the purpose of planning or performing the audit" (IAASB, DAWG, 2016, p. 7). In general, data analytics refers to data sources and the techniques of data analysis.

Audit clients have begun to make use of data in a variety of ways as the quantity of data increases and structured data is more readily available in real-time or at the day-to-day level. Unstructured, often non-financial data from outside the client organization is also used more frequently. This can include textual data, such as emails, web pages, Twitter, Facebook, and Google, as well as videos, images, and audio data (Alles & Gray, 2016; Teoh, 2018). The use of this disaggregated client data contributes significantly to the discovery of anomalies, which are more effective at a daily level than on a weekly, monthly, or annual level. In this case, the use of disaggregated data is a primary driver of audit effectiveness (Kogan et al., 2014). This progression fueled the usage of advanced ADA techniques (e.g., process mining, text mining, visualization, and predictive analytics). Overall, advanced techniques hold the potential to change audit practices fundamentally, despite their rare use in audit practice currently, especially in small audit firms (Eilifsen et al., 2020; Henry et al., 2023).

Audit-related research from recent ADA developments is mostly conceptual, often describing ADA characteristics via various examples, discussing their current development and potential obstacles, and pointing out areas requiring further research. Recent empirical studies are often survey- or interview-based. These exploratory studies primarily focus on the emergence of recent ADA techniques in auditing (for an overview, see Ruhnke, 2023a). In addition, research based on experiments, archival studies, and case studies sheds light on isolated, narrowly defined issues. Examples include the timing of the use of data visualizations in the audit process (Rose et al., 2017), the use of predictive ADA techniques for fraud detection (Perols et al., 2017), the use of weather and social media data to develop an expectation for retail revenues and provisions (Steinker et al., 2017), or the use of environmental data (e.g., CO_2 emissions) to detect inconsistencies between these data and financial statement data like revenues (Ruhnke & Salender, 2023).

Other research areas related to ADA concern audit quality, education matters, and technical audit standards (Ruhnke 2023a). The lack of audit regulations specific to ADA often causes confusion and frustration (Austin et al., 2021). Conceptional issues relate to the audit process, materiality considerations, and the audit risk model, among others. When using the entire population of transaction data, new risks (e.g., outlier risks) become evident, and the reliability of the data inputs for conducting analytical procedures or risk assessments might be challenging (Ruhnke, 2023b). With regard to the audit risk model, the character of the audit process might change from a sample-driven process to a more data-driven one (Appelbaum et al., 2017). Although the IAASB (2022, p. 3) has stated that "the overall audit risk model has not changed", it is expected that innovative data analytics technologies have the potential to change the perspective of the current audit risk model and its application (for a discussion, see Ruhnke, 2023c). Overall, ADA offers several challenging research perspectives for developing these technologies, supporting audit firms with their application, and supporting the standard setter (for an overview of future research areas, see Ruhnke 2023a, Appendix B).

Artificial Intelligence

One of the emerging technologies which has the potential to yield to a disruptive reframing of existing audit methodologies is usually referred to as Artificial Intelligence (AI) (Kokina & Davenport, 2017; Seidenstein et al., 2024). AI is a broad research area which can be generally described as the modeling of human-like intelligence (Russell & Norvig, 2022). One subcategory of AI is Machine Learning (ML), focused on a data intensive training of the algorithms' functionalities instead of explicitly coding them (Samuel, 1959). Most recent advances in AI are attributable to the research area of Deep Learning (DL), which represents a subfield of ML. DL employs deep neuronal network architectures for specific downstream tasks. These models are based on complex model architectures, which are conceptionally inspired by the functionalities of a human brain (LeCun et al., 2015).

Existing research in AI investigates the disruptive potential of AI for all phases of a risk-based audit, which can be broadly defined as risk assessment, control evaluation, and substantive procedures.

During *Risk Assessment*, an auditor needs to determine the likelihood and magnitude of risks of material misstatements in the financial statements (ISA 315 (Revised 2019), IAASB, 2019). AI can enhance the phase of *Risk Assessment* by the allocation of specific audit engagements to risk categories determined by the extraction of relevant insights out of brainstorming sessions (Li & Liu, 2020). Such an extraction necessitates in advance, that the sessions are recorded. Additionally, to name some further examples, conference calls or quarterly earnings disclosures can be analyzed to extract sentiment as an indicator to determine an initial risk-level for a specific audit engagement (Siano & Wysocki, 2019; Huang et al., 2021).

Internal Control Evaluation focuses on the functionality of the internal control system to detect control deficiencies, which reduces the chance that material misstatements were prevented or timely detected (ISA 315 (Revised 2019), IAASB, 2019). DL is capable of analyzing documents, e.g., order approvals, for a necessary signature in alignment with internal control policies (Sun, 2019). Furthermore, Zhaokai & Moffitt (2019) developed a framework how to analyze contracts with the help of AI. These are just some examples how AI can augment existing risk-based auditing.

The phase of *Substantive Procedures* is merely about conducting audit tasks to obtain sufficient appropriate audit evidence (ISA 330, IFAC, 2009a; ISA 500, IFAC, 2009b). It is shown that AI is able to conduct anomaly detection (Schreyer et al., 2018) and to audit inventories via drone observation with subsequent AI-based analytics (Christ et al., 2021). A further example for the application of DL can be described by their ability to supplement auditors in the conduction of efficient audit sampling (Schreyer et al., 2022).

During the several phases of a risk-based audit, the auditor evaluates the sufficiency and appropriateness of the obtained audit evidence out of the conducted substantive procedures (ISA 500, IFAC, 2009b) and assembles its findings in an audit report (ISA 700 (Revised), IAASB, 2015). Decision support functions associated with DL can help an auditor assess if reasonable assurance has already been obtained or if there is a need to conduct additional audit procedures (Sun, 2019). Furthermore, AI has the potential to support the audit of disclosures in the notes. For example, Ramamurthy et al. (2021) illustrate how to enhance effectiveness and efficiency with AI in the audit of such disclosures. This can be done by an automatic mapping of the regulatory requirements to the specific text excerpts out of the notes.

Moreover, the most potential for innovative advances in AI are attributable to Generative AI (GenAI; Feuerriegel et al., 2024) which is capable to generate content based on interactions with a human, such as ChatGPT (OpenAI, 2023). The significant breakthroughs associated with GenAI are attributable to its functionality in solving tasks without having been trained for these tasks (Bommassani et al., 2022). This means, that models of GenAI need no specialized training to accomplish a task. Instead, they just must be fine-tuned with a few examples to solve a specific downstream task (Brown et al., 2020). There is already some research on GenAI regarding how to serve as a co-pilot for an auditor during a financial statement audit (Gu et al., 2023) or how to implement GenAI's underlying models within organizations from a technical and strategic perspective (Föhr et al., 2023b). Such research focuses on the performance of complex audit tasks that can be solved with GenAI, such as financial ratio analysis with subsequent interpretations by a GenAI model (Gu et al., 2023) or the automatic audit of provisions according to German Commercial Code (Föhr et al., 2023a).

Assurance on Sustainability Reports

Regulators determine the total number of statutory audits. Therefore, the market for audit services has limited growth opportunities. As a consequence, non-audit services become increasingly important for audit firms (Wirtschaftsprüferkammer, 2023). Apart from tax advisory and other consulting services, audit firms offer other assurance services. Such services comprise, for example, assurance on management systems (compliance, risk, internal control), outsourced internal audits, review engagements, assurance related to IT and cyber security, or assurance on non-financial information, like sustainability reports.

According to the EU Non-Financial Reporting Directive, statutory auditors and audit firms should only check that the non-financial statement has been provided (European Parliament & European Council, 2014). However, Member States had the option to require an independent assurance provider to verify the information. Only France, Italy, and Spain used this option. Moreover, many companies located in other EU Member States voluntarily demanded such services.

In 2022, the EU adopted the Corporate Sustainability Reporting Directive (CSRD) (European Parliament & European Council, 2022). It greatly expanded the number of companies obliged to prepare sustainability reports and implemented mandatory limited assurance engagements regarding the compliance of sustainability reporting with legal requirements. Until 1 October 2028, the European Commission will decide whether it is feasible for assurance providers to express an opinion about the compliance of the sustainability reporting with requirements based on a reasonable assurance engagement. Furthermore, the Directive includes the Member State options to allow an audit firm other than the one carrying out the statutory audit of financial statements or an independent assurance services provider to assure sustainability reporting.

Prior research intensively investigated the impacts of assurance on sustainability/Corporate Social Responsibility/Environmetal Social and Governance reports. It predominantly revealed positive effects, i.e., a higher report quality (e.g., Michelon et al., 2019), increased credibility of the report (e.g., Phang & Hoang, 2021), an improved sustainability reputation of the reporting firm (e.g., Reimsbach et al., 2018), a higher likelihood to invest (e.g., Shen et al., 2017) and for getting loans (Quick & Inwinkl, 2020), easier access to capital (e.g., Carey et al., 2021), and improved analysts' forecasts (e.g., Zhou et al., 2019). Likewise, there is previous research evidence that such positive consequences of assurance are stronger if the assurance is provided by a public accounting firm and not by an alternative assurance provider. In that case, report quality (e.g., Sierra-García et al., 2022) and the perceived credibility of sustainability reports (Pflugrath et al., 2011) are higher, assurance (e.g., Martínez-Ferrero & García-Sánchez, 2018) and assurance report quality (e.g., Bollas-Araya et al., 2019) are superior, cost of equity is lower (e.g., Martínez-Ferrero & García-Sánchez, 2018), the likelihood for getting loans increases (Quick & Inwinkl, 2020), access to finance is easier (Carey et al., 2021), and analysts' forecasts are improved (Casey & Grenier, 2015). Concerning the assurance level, some research studies indicated that addressees of sustainability reports may be unable to understand different assurance levels (Roebuck et al., 2000; Hasan et al., 2003; Schelluch & Gay, 2006; Low & Boo, 2012). However, other studies demonstrate that assurance's positive impacts are more substantial or can only be identified in the case of reasonable assurance. Research revealed a higher report credibility (Sheldon & Jenkins, 2020), an improved sustainability performance (Rohani et al., 2023), a higher willingness to invest (Gerwanski et al., 2021), more favorable decisions by bankers (Quick & Inwinkl, 2020), a higher perceived firm value (Hoang & Trotman, 2021), a higher likelihood for investment recommendations by financial analysts (Rivière-Giordano et al., 2018), and improved analysts' forecasts (Cuadrado-Ballesteros et al., 2017).

These findings support the EU's decision to require mandatory assurance. In contrast, the Member State option to allow alternative assurance service providers can be criticized because this would result in lower benefits to the reporting firm. Similarly, requiring only limited assurance in the beginning can be detrimental. However, prior research was typically associated with voluntary assurance provision, and mandatory assurance services could have different impacts.

Another strand of prior research investigated the determinants of assurance quality. However, these studies primarily proxy assurance quality via the completeness of the assurance report, a potentially weak indicator (e.g., Rossi & Tarquinio, 2017; Vaz Ogando et al.; 2018; Martínez-Ferrero et al., 2018; García-Sánchez, 2020). Many quality proxies frequently applied to financial statement audits (e.g., earnings management and earnings quality, going concern opinions, internal control weaknesses) do not apply to sustainability report assurance. Thus, future research must develop alternative meaningful surrogates. Another promising avenue for future research would be identifying factors affecting assurance quality (e.g., fees, tenure, industry expertise).

The CSRD has introduced a large amount of new assurance engagements. This raises the question of whether assurance providers' quantitative and qualitative capacity is sufficient to satisfy such additional demand. It is unclear whether audit firms have enough staff with appropriate expertise and whether they can increase their capacity in the short term. Another interesting question is whether public accounting firms cooperate with specialist consulting firms or will do so in the future and how such cooperation will be designed. In the future, the public register of statutory auditors shall contain whether the statutory auditor is also approved to carry out the assurance of sustainability reporting. To be registered, a candidate must prove the theoretical knowledge in an exam and prove at least eight months of related practical training. Considering that financial statement auditors typically must prove three years of practical training, it is questionable whether appropriate expertise can be acquired in such a short period.

Against this backdrop, the special issue at hand presents three research papers on the use of disruptive technologies in auditing and internal auditing. The article by *Eulerich/Kasper/Sofla* uses an experiment to investigate whether continuous auditing and a (COVID-19) crisis interact with the conscientiousness of audited bodies and how this affect compliance with internal controls. *Feliciano/Quick/Eulerich* apply a survey to examine the future relevance of selected digital tools to internal auditing and the self-assessment of internal auditors' level of related expertise. *Föhr* 's contribution develops a comprehensive categorization and classification method that enables a systematic classification of artificial intelligence technologies in terms of their degree of application for a risk-oriented audit. The method developed was comprehensively evaluated with experts from the field.

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