

The impacts of the use of data analytics and the performance of consulting activities on perceived internal audit quality

Use of data analytics

Received 21 August 2022
Revised 22 January 2023
7 April 2023
Accepted 1 May 2023

Nathanaël Betti

*Louvain Research Institute in Management and Organizations,
Universite catholique de Louvain, Louvain-la-Neuve, Belgium*

Steven DeSimone

*Department of Economics and Accounting, College of the Holy Cross,
Worcester, Massachusetts, USA*

Joy Gray

*Department of Accounting, Bentley University,
Waltham, Massachusetts, USA, and*

Ingrid Poncin

*Louvain Research Institute in Management and Organizations,
Universite catholique de Louvain, Mons, Belgium*

Abstract

Purpose – This research paper aims to investigate the effects of internal audit's (IA) use of data analytics and the performance of consulting activities on perceived IA quality.

Design/methodology/approach – The authors conduct a 2×2 between-subjects experiment among upper and middle managers where the use of data analytics and the performance of consulting activities by internal auditors are manipulated.

Findings – Results highlight the importance of internal auditor use of data analytics and performance of consulting activities to improve perceived IA quality. First, managers perceive internal auditors as more competent when the auditors use data analytics. Second, managers perceive internal auditors' recommendations as more relevant when the auditors perform consulting activities. Finally, managers perceive an improvement in the quality of relationships with internal auditors when auditors perform consulting activities, which is strengthened when internal auditors combine the use of data analytics and the performance of consulting activities.

Research limitations/implications – From a theoretical perspective, this research builds on the IA quality framework by considering digitalization as a contextual factor. This research focused on the perceptions of one major stakeholder of the IA function: senior management. Future research should investigate the perceptions of other stakeholders and other contextual factors.

Practical implications – This research suggests that internal auditors should prioritize the development of the consulting role in their function and develop their digital expertise, especially expertise in data analytics, to improve perceived IA quality.

Originality/value – This research tests the impacts of the use of data analytics and the performance of consulting activities on perceived IA quality holistically, by testing Trotman and Duncan's (2018) framework using an experiment.



Introduction

The trend toward digitalization has permeated all industries (Verhoef *et al.*, 2021) and has led organizations to adopt and use digital technologies to provide new, value-producing opportunities (Christ *et al.*, 2019). Among digital technologies, organizations are planning to further integrate the use of data analytics (Betti *et al.*, 2021; PwC, 2018). Digitalization can positively affect corporate processes, operational activities and customer interactions (Verhoef *et al.*, 2021) by facilitating process standardization (Kokina and Blanchette, 2019; Troshina and Mantulenko, 2019). Nevertheless, over the past decade, digitalization has also brought challenges and risks related to volatility, uncertainty and ambiguity (Schoemaker *et al.*, 2018), increasing the demand for consulting activities (Betti *et al.*, 2021).

Digitalization trends have attracted the attention of management, boards and regulators (ECIIA, 2019; Kane *et al.*, 2016). In recent surveys, board members and top management identify performance expectation shortfalls and competing with “born digital” organizations as top risks (Protiviti and North Carolina State University, 2019), while two out of three internal audit functions (IAFs) report they will undertake digital transformation initiatives (ECIIA, 2019). IAFs are at the forefront of digitalization, and top managers expect IAFs to bring value by adopting a consulting role to help them face the challenges, risks and strategy of digitalization. Management also expects IAFs to leverage the potential of digital technologies by using tools such as data analytics in their internal audit (IA) missions (Betti and Sarens, 2021; Betti *et al.*, 2021). Providing value to organizations is essential for the IAF to remain relevant (Castanheira *et al.*, 2010; Garven and Scarlata, 2020; Lenz and Hoos, 2023; Soh and Martinov-Bennie, 2011; Stewart and Subramaniam, 2010). As a non-mandated function in most contexts, internal auditors cannot afford a narrow focus based only on evaluating and strengthening internal controls (Brody and Lowe, 2000; Cashell and Aldhizer, 2002; Cohen *et al.*, 2004; Erasmus and Coetzee, 2018; EY and Forbes, 2017; Gramling *et al.*, 2004). The institute of internal auditors (IIA’s) definition of internal auditing (Institute of Internal Auditors, 2017) stresses that IAFs provide consulting services in addition to more traditional assurance services, a practice that has existed in leading IAFs for many years (Garven and Scarlata, 2020; Nagy and Cenker, 2002). Consulting services, which often include serving an advisory role in new system implementation projects as well as risk identification and mitigation activities, are typically seen as value-added by top managers (Betti and Sarens, 2021; Betti *et al.*, 2021; Ege *et al.*, 2022; Lenz and Hoos, 2023; Volodina *et al.*, 2022; Yang, 2021). Top managers wants the IAF to become more of a business partner by performing consulting activities to support strategic risks and initiatives (Betti *et al.*, 2021). Digitalization has changed management’s expectations, and IAFs are uniquely positioned to identify, understand and help organizations manage the risks and opportunities that arise from digitalization (Betti *et al.*, 2021). IAFs have an enterprise-wide perspective, apply a risk-management approach and continuously search for control weaknesses while also identifying efficiency opportunities (Protiviti, 2019a; Volodina *et al.*, 2022). Thus, IAFs are able to simultaneously observe and analyze the organization’s digital landscape from both a strategic and an audit and control perspective.

Digitalization also encourages the IAF to reconfigure its way of working by adopting digital technologies, such as data analytics, in its audit missions (Betti *et al.*, 2021; Islam and Stafford, 2022). The use of data analytics helps IAFs innovate, improves decision-making and increases agility in the face of digital disruptions (Institute of Internal Auditors, 2018). Data analytics also enables continuous auditing in areas such as

compliance and financial reporting controls, freeing IAF time to focus on high-risk and value-added areas such as cybersecurity and strategic risk (ECIIA, 2019). Shifting to higher value-added activities with a focus on risk is consistent with the Institute of Internal Auditors' (Institute of Internal Auditors, 2019) recommendation that IAFs use data analytics to identify and monitor precursors to risks.

By performing consulting activities and using digital technologies, the IAF is expected to add value to organizations (Betti and Sarens, 2021), which is a key dimension of the broader multi-dimensional concept of IA quality (Trotman and Duncan, 2018). In their qualitative research, Trotman and Duncan (2018) have identified contextual factors as an important variable that influences perceived IA quality. Prior research (Betti and Sarens, 2021; Betti *et al.*, 2021) highlights digitalization and the nature of engagement (consulting and assurance) as two key contextual factors influencing the IAF's work. Nevertheless, we still have limited knowledge on the impact of these two contextual factors on IA quality. Specifically, Trotman and Duncan (2018) call for research on the impact of the contextual factor of the nature of engagement (consulting and assurance) on IA quality. In addition, Betti *et al.* (2021) call for research on the effect of using both digital technologies and consulting activities performed by the IAF on perceived IA quality. To address these calls, this paper investigates the effect of digitalization, specifically the use of data analytics [1] by the IAF, and the performance of consulting activities, on managers' perception of IA quality using a 2 (presence versus absence of data analytics) $\times$ 2 (presence versus absence of consulting activities) between-subjects experimental design. Our study is timely as significant variability remains in IAF capabilities in and use of data analytics as well as the nature of engagement activities performed by the IAF.

In the following sections, we present the theoretical background and study methodology. Then, we report and discuss the results. Finally, we present the theoretical and managerial implications of our results and discuss future research avenues.

Theoretical background

Internal audit quality framework

The ability of the IAF to add value to the organization is an important dimension of the broader multi-dimensional concept of IA quality (Trotman and Duncan, 2018). Prior research largely explores the concept of quality from an external audit perspective (e.g.: Glover *et al.*, 2008; Messier *et al.*, 2011; Pizzini *et al.*, 2015), focusing on the external auditors' assessments of the IAF's input (competence, objectivity and independence). However, these studies do not capture fully the construct of IA quality (Trotman and Duncan, 2018). Recently, Trotman and Duncan (2018) developed an integrative multi-stakeholder IA quality framework, based on the external audit quality frameworks of Knechel *et al.* (2013) and IAASB (2014). Based on their model, IA quality assessment encompasses four dimensions: the input, the process, the output and the outcome (Trotman and Duncan, 2018). The input dimension refers to the assessment of the IAF attributes; which include technical skills, objectivity, experience, soft skills and personality traits. The process dimension relates to the assessment of quality indicators, including technical audit production quality and service interaction quality [2]. The output dimension refers to the assessment of the IAF's ability to produce reports including effective communication, as well as quality, relevant and pragmatic findings and recommendations. Finally, the outcome dimension relates to the ability of the IAF to create value, which happens when an audit positively affects change within the organization (Trotman and Duncan, 2018).

Each of these dimensions of IA quality can be impacted by contextual factors (Trotman and Duncan, 2018). In their study, Trotman and Duncan (2018) identify the organization's culture, the use of the IAF as a management training ground and the access to appropriate staff as contextual factors. As other contextual factors can influence the dimensions of the IA

quality, prior research (Betti and Sarens, 2021; Betti *et al.*, 2021; Trotman and Duncan, 2018) calls for further investigation of the impact of contextual factors on the IA quality with experiments. Specifically, Trotman and Duncan (2018) suggest to explore the effect of the nature of engagement (assurance and consulting activities) on the IAF. Furthermore, Betti *et al.* (2021) suggest examining the effect of using both digital technologies and consulting activities performed by the IAF on perceived IA quality. Given the importance of these two contextual factors on the IAF, this paper aims to investigate the effect of digitalization; specifically the effect of a popular and expanding digital technology: data analytics (Betti and Sarens, 2021; Betti *et al.*, 2021; Koreff *et al.*, 2021; Krieger *et al.*, 2021; Rakipi *et al.*, 2021) and the performance of consulting activities on perceived IA quality. Therefore, as the framework developed by Trotman and Duncan (2018) covers IA quality concepts and stresses the importance of contextual variables, we expand on it in our study. Figure 1 presents the IA quality framework developed by Trotman and Duncan (2018), adding the consulting and data analytics factors investigated by this paper.

Digitalization as contextual factor

Digitalization is defined as “the manifold sociotechnical phenomena and processes of adopting and using these technologies in broader individual, organizational and societal contexts” (Legner *et al.*, 2017, p. 301) and therefore describes the way organizations adopt and use digital technologies to provide value-producing opportunities (Christ *et al.*, 2019; Verhoef *et al.*, 2021).

Digitalization is not a new phenomenon (Mertens and Wiener, 2018). The business environment has faced several waves of digitalization, including emergence of computers for business use and the internet. Today, digitalization includes the introduction of social, mobile, analytics and cloud computing, which leads organization to adapt their processes and tasks (Bouwman *et al.*, 2018; Canning *et al.*, 2018; Legner *et al.*, 2017; Verhoef *et al.*, 2021).

Organizations increasingly implement and use digital technologies, such as data analytics, to automate and facilitate day-to-day work (Betti and Sarens, 2021; Legner *et al.*, 2017). The American Institute of Certified Public Accountants defines data analytics as:

The science and art of discovering and analyzing patterns, identifying anomalies, and extracting other useful information in data underlying or related to the subject matter of an audit through analysis, modeling, and visualization of planning or performing the audit (AICPA, 2017, p. 1).

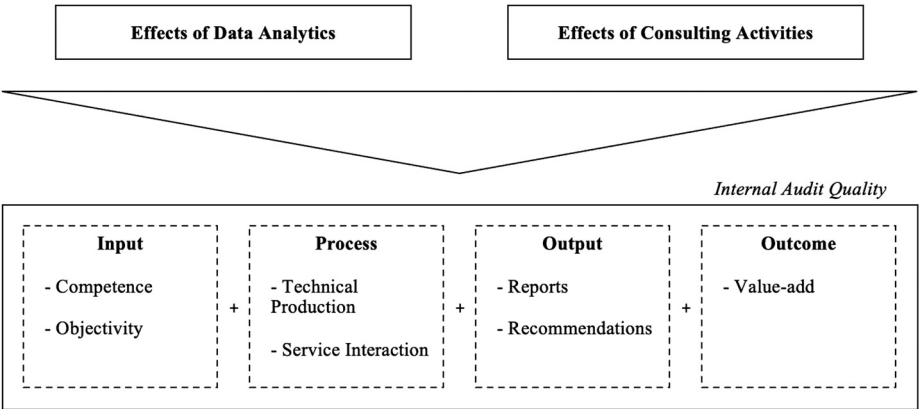


Figure 1.
Multi-stakeholder IA
quality framework
and digitalization

Source: Created by authors

In 2018, worldwide digital data represented 33 zettabytes (three trillion gigabytes), and it continues to grow rapidly (IDC, 2018), reaching approximately 64 zettabytes in 2022 (Bartley, 2022). This volume of data, coupled with the velocity of data collection and availability, positions data analytics as a powerful tool that allows the integration and utilization of a variety of structured and unstructured data from both internal and external sources. This enables internal auditors to provide important insights to decision-makers by using data analytics to perform advanced analyses on large, unstructured sets of data (Betti and Sarens, 2021; Islam and Stafford, 2022; Rickett, 2016; Tschakert *et al.*, 2016). Data analytics enables both advanced analyses of past events and predictive analyses of future events (i.e. through simulations or clustering) (Al-Htaybat and von Alberti-Alhtaybat, 2017; Lee *et al.*, 2014; Mariani and Wamba, 2020; Rickett, 2016; Tschakert *et al.*, 2016). Data analytics may therefore be used during different points of the IA process including the planning, execution and/or follow-up phases (Betti and Sarens, 2021; Tang *et al.*, 2017; Wang and Cuthbertson, 2015). Performing analyses on all available data could help the IAF make more precise assessments, plan better testing to meet audit objectives, provide insights about future events and facilitate the organizational decision-making process (Al-Htaybat and von Alberti-Alhtaybat, 2017; Betti and Sarens, 2021; Gandomi and Haider, 2015; Rickett, 2016). Thus, data analytics can help IAFs add value to organizations and allow greater IAF alignment with the business (Betti and Sarens, 2021; Betti *et al.*, 2021; PwC, 2018).

However, internal auditors still struggle to integrate digital technologies into their work (PwC, 2019). Approximately half of internal auditors do not use, but intend to use emerging technologies such as artificial intelligence and robotic process automation in the coming years. Nevertheless, many IAFs have integrated data analytics into their work, especially in audit planning and execution (PwC, 2019). In a 2018 IIA survey, approximately 60% of chief audit executives stated that their IAFs had fully or partially implemented data analytics (Institute of Internal Auditors, 2018). However, only 30% of chief audit executives reported harnessing the full potential of data analytics (Institute of Internal Auditors, 2019). Therefore, despite multiple stakeholders believing in the value of data analytics, there are mixed findings regarding the actual use of data analytics by IAFs.

In addition to the use of data analytics by IAFs, the performance of consulting activities is an important contextual factor to consider in evaluating IA quality (Betti and Sarens, 2021; Trotman and Duncan, 2018).

Consulting as contextual factor

Over the years, IAF engagements have evolved to meet the requirements of the changing business environment (Castanheira *et al.*, 2010; Soh and Martinov-Bennie, 2011). IAFs have moved from strictly assurance activities, focused on internal controls, to a mix of assurance and consulting activities, including more advisory activities (Betti and Sarens, 2021; Ege *et al.*, 2022; Lenz and Hoos, 2023; Roussy and Perron, 2018). Some prior research has highlighted that performing both assurance and consulting activities could lead the IAF to jeopardize its independence and objectivity (Lenz and Hahn, 2015; Roussy, 2013; Soh and Martinov-Bennie, 2011). However, recent research has stressed the importance of the IAF's performance of consulting and advisory activities. Through these activities, IAFs assist the organization in proactively dealing with risk and improving business efficiency, especially in a digitalized business environment (Betti and Sarens, 2021; Jones *et al.*, 2017; Volodina *et al.*, 2022). Digitalization induces higher volatility, uncertainty, complexity and ambiguity (Schoemaker *et al.*, 2018) and therefore generates emerging risks that the IAF needs to help organizations determine how to best manage them (Betti and Sarens, 2021). Given the pervasive impact of digital technologies on society, the IAF can position itself through

consulting as a digital change agent helping to monitor emerging risks (i.e. cybersecurity, data privacy) while bringing value to organizations (Betti and Sarens, 2021; Castanheira *et al.*, 2010; Chapman, 2001; Soh and Martinov-Bennie, 2011; Stewart and Subramaniam, 2010).

Research suggests that senior management desires more support and guidance from the IAF on digital matters (Betti and Sarens, 2021; D'Onza *et al.*, 2015; Roussy, 2013). Examples of this include advising senior management on cybersecurity programs, governance and risk management, (Dixon and Singer, 2011; Kahyaoglu and Caliyurt, 2018) and new technology implementation (Flora and Rai, 2015).

However, we still have limited knowledge about how the performance of consulting activities (Betti *et al.*, 2021; Roussy and Perron, 2018; Trotman and Duncan, 2018) and the use of data analytics (Betti *et al.*, 2021) affect perceived IA quality, especially from stakeholders others than external auditors (Trotman and Duncan, 2018). The assessment of IA quality differs depending on the IAF's major stakeholders (Oussii and Boulila Taktak, 2018; Trotman and Duncan, 2018). Therefore, the IAF's major stakeholders, including in-house/co-sourced/outourced internal auditors, the audit committee, senior management and external auditors, do not use a common method to assess IA quality and tend to emphasize different dimensions depending on the lens through which they form their judgment (Trotman and Duncan, 2018). For example, external auditors focus most on the input dimension, specifically the extent to which the IAF is objective [3], while senior management focuses on the ability of the IAF to create value for the organization (the outcome dimension). In-house internal auditors tend to consider their IAF as high quality when everything possible is done in relation to the IA process dimension to ensure a complete audit engagement, which is operationalized by the process dimension of the IA quality framework (Trotman and Duncan, 2018).

In this paper, we test whether the use of data analytics and the performance of consulting activities alter the perceptions of IA quality by a key stakeholder: managers.

Hypotheses

Perceptions of IA quality differ between stakeholders as they have diverse needs and views (Cohen *et al.*, 2004; Cohen *et al.*, 2013; Erasmus and Coetzee, 2018; IAASB, 2014; Trotman and Duncan, 2018). Until recently, IA quality research focused almost solely on competence, objectivity and work performance (Bame-Aldred *et al.*, 2013; Gramling *et al.*, 2004; Lesage and Ben Saab, 2009; Prat Dit Hauret, 2003). Roussy and Brivot (2016) found that stakeholder perceptions of IA quality are more complex than what is suggested in that literature, and Trotman and Duncan (2018) built on that research to develop the aforementioned multi-stakeholder model of IA quality, which found that stakeholders consider technical skills to be the foundation of a high-quality IAF. While in their study participants indicate that IAFs generally possess the necessary technical skills, and despite recent research that investigates the use of data analytics by IAFs [4], Trotman and Duncan (2018) did not specifically consider digitalization and the use of data analytics. In contrast, more than 50% of surveyed chief audit executives indicated that data mining and analytics are essential for an IAF to properly discharge its duties (Institute of Internal Auditors, 2018). According to chief audit executives who were surveyed regarding the use of enabling technologies, data analytics is used with the greatest frequency and IAFs derive the highest relative value therein (Protiviti, 2019b). However, even when used, data analytics is typically incorporated by IAFs as a point solution rather than as part of a broader initiative (Protiviti, 2018).

The use of data analytics requires that an IAF possesses technical skills (IA quality framework input measure) (Abdelrahim and Al-Malkawi, 2022; Islam and Stafford, 2022).

Trotman and Duncan (2018) also identify technical production (IA quality process measure) as a main indicator of quality within IAF processes. Their interviewees noted the value of and preference for a risk-based strategic audit approach over a compliance-based “tick-and-flick” audit approach, as risk-based auditing allows IAFs to identify organizations’ biggest risks while balancing time and resources effectively (Christ *et al.*, 2019; ECIIA, 2019). Data analytics enables a more efficient risk-based approach by allowing IAFs to perform risk profiling, test data simulation and statistical sampling during the planning stages of the audit (Islam and Stafford, 2022; Protiviti, 2018). Also, data analytics enables IAFs to perform full population testing, continuous controls monitoring, fraud indicator assessment, predictive risk identification and control simulation during the audit execution stage (Christ *et al.*, 2019; ECIIA, 2019; Protiviti, 2018). Furthermore, the use of data analytics for auditing compliance and financial reporting controls can free up IA’s time to focus on high-risk areas such as cybersecurity or strategic risks (ECIIA, 2019). Board members and top management recognize the value of data analytics as they view their use as a key element of managing operations and strategic risks (Protiviti and North Carolina State University, 2019). Internal auditors possess a unique view of the organization from both risk and strategic perspectives. Thus, internal auditors that are both engaged in consulting activities as a trusted advisor to management, and are able to use the power of data analytics to analyze large data sets, can increase their value-add in the eyes of management.

Data analytics may also improve the quality of IAF reporting (IA quality framework output measure) by allowing for risk quantification, real-time exception management and root-cause investigation (Islam and Stafford, 2022; Protiviti, 2018). As reports that include these elements are more useful to stakeholders, IAFs should therefore be viewed as value-adding (IA quality framework outcome measure) when using data analytics. Prior research in external auditing indicates that the use of digital technologies and data analytics may increase the quality of the external audit engagements by analyzing full data sets instead of limiting the testing to samples (Earley, 2015; Islam and Stafford, 2022; Manita *et al.*, 2020). When combined, the preceding suggests that the use of data analytics by IAFs will increase perceived IA quality from all stakeholder perspectives across all four dimensions of IA quality.

However, prior research also finds that IAF use of data analytics creates challenges, including stakeholder frustration caused by insufficient time to perform other types of audits and increased staff turnover as analytics-savvy internal auditors are poached internally for management positions or by other companies. This may lead to client frustration and a decrease in perceived IA quality (Christ *et al.*, 2019). If internal auditors lack data analytics proficiency and/or business acumen, they are less likely to ask the correct questions and use the correct analyses, and thus may investigate the wrong things. This can result in less relevant recommendations and ultimately decrease managers’ perception of IA quality.

Despite these challenges, we argue that the potential benefits of IAF use of data analytics outweigh these drawbacks. Thus, we pose our first hypothesis:

- H1. Perceived internal audit quality will be higher when internal auditors use data analytics than when internal auditors do not use data analytics.

Since the IIA added consulting activities to the definition of IA in 2000 (Rittenberg and Covalesski, 2001), many concerns have been voiced about the effect on internal auditor objectivity (i.e. Lenz and Hahn, 2015; Roussy, 2013; Soh and Martinov-Bennie, 2011). However, Trotman and Duncan (2018) found that some stakeholders consider objectivity to be a mindset. This contrasts with previous research which used proxies for objectivity via

an IAF’s organizational independence (Ege, 2015; Lin *et al.*, 2011; Prawitt *et al.*, 2012). The mindset viewpoint is consistent with objectivity as defined in IIA audit standards and suggests added value when IAFs work closely and have strong relationships with management (Abdelrahim and Al-Malkawi, 2022). Consultancy projects related to strategic activities indicate that the IAF has access to and is favorably viewed by the highest-level managers in the organization (Roussy and Brivot, 2016), who would like the IAF to become more of a business partner (Betti and Sarens, 2021). This suggests that consultancy activities by IAFs may not lead to a decrease in perceived quality.

We therefore expect that IAF involvement in consultancy activities will have a positive effect on management perceptions of IA quality as these activities are considered value-added. Thus, we pose our second hypothesis:

H2. Perceived internal audit quality will be higher when internal auditors perform consulting activities than when internal auditors do not perform consulting activities.

Above, we posit that IAF use of data analytics increases the perception of IA quality through increased efficiency, the ability to analyze a larger portion of the population and the use of predictive analytics to recommend strategic actions. We also posit that the performance of consulting activities signals both a favorable perception of the IAF and a stronger management/IAF relationship. Data analytics guidance suggests that among the more challenging aspects of data analytics is the ability to investigate the relevant data and perform the right analyses (Al-Htaybat and von Alberti-Alhtaybat, 2017). The benefits of organizational knowledge from consulting activities, coupled with the benefits of efficiency and insight provided by IAF use of data analytics, should result in an interaction effect on the perception of IA quality. Specifically, we posit that the use of data analytics will increase the effect of consulting activities on IA quality:

H3. When internal auditors perform consulting activities, perceived IA quality will be higher when internal auditors use data analytics than when internal auditors do not use data analytics.

Methodology

Participants and procedure

We conduct a 2 (presence versus absence of data analytics) × 2 (presence versus absence of consulting activities) between-subjects experiment. Figure 2 presents the manipulations of the experimental design.

Condition 1 - No Consulting - No Data Analytics	Condition 2 - No Consulting - Yes Data Analytics
Condition 3 - Yes Consulting - No Data Analytics	Condition 4 - Yes Consulting - Yes Data Analytics

Figure 2.
Manipulations of the
experimental design

Source: Created by authors

Middle and upper manager participants who worked in the USA were recruited using Prolific [5] (Peer *et al.*, 2017) in 2020. Prior research has shown that responses collected from online platforms are of similar quality to responses provided in laboratory experiments (Goodman *et al.*, 2013). Among online research platforms, the literature (Palan and Schitter, 2018) recommends to use the Prolific platform that explicitly informs participants that they are recruited for research purposes and enables good recruitment standards for researchers. The case and the related survey were provided to participants via an electronic link. After reading the consent form, participants were randomly assigned to one of the four case conditions and presented with one of the four scenarios containing information about Electronic Retail Inc., a fictional organization. After reading the scenario, identical questions were presented to each participant. We investigate managers' perceptions as the most diverse stakeholder given the broad mandate of internal auditing. Management is concerned with both assurance and consultancy in terms of value added. We used both upper and middle managers as both are likely to have engaged with internal auditors. This is consistent with prior studies which have used managers in experiments to investigate their perceptions of IAFs (Brown and Fanning, 2019; Farkas *et al.*, 2019).

Total, 126 participants participated in the study. Before analyzing the data, we removed six participants who did not complete the full questionnaire (Mursita and Nahartyo, 2022; Santos and Beuren, 2022). After this data cleansing, 120 valid questionnaires remained.

Table 1 presents participants' descriptive statistics. They averaged just over six years of experience in their current role. Almost 67% of respondents were business managers in privately held organizations and approximately 16% worked in publicly traded organizations. The remaining participants are almost evenly divided between not-for-profit and public sector organizations. The majority, 61%, of the respondents were male. Respondents self-reported a high level of knowledge of digital technologies (an average of 7.97 on a 0 to 10 Likert scale). Knowledge was measured by four items, adapted from Rose *et al.* (2012). To create a single measurement of knowledge of digital technologies, we performed a factor and reliability analysis to confirm that the four items represent a single underlying construct (Santos and Beuren, 2022), using a principal component analysis (PCA). Only one factor was extracted from the exploratory factor analysis, whose percentage of explained variance was 83.74%. The Cronbach's alpha was 0.933. Therefore, the scale explained more than 55% of the variance and achieved a Cronbach's alpha value greater than the recommended minimum value of 0.7 (Leclercq *et al.*, 2018; Nunnally, 1978; Santos and Beuren, 2022). Thus, we grouped the four items under one single factor

Variable	<i>N</i>	%	Min	Max	Mean	SD
Years of experience in the current position			1	32	6.08	4.20
Knowledge of digital technologies			2.50	10	7.97	1.70
<i>Type of organization</i>						
Non-for-profit organization	11	9.17				
Privately held (non-listed) organizations	80	66.67				
Public sector	10	8.33				
Publicly traded	19	15.83				
<i>Gender</i>						
Female	47	39.17				
Male	73	60.83				

Source: Created by authors

Table 1.
Description of
participants
(*N* = 120)

describing the global level of knowledge of participants. Table 2 presents the descriptive statistics of the digital knowledge items. Panel A in Table 3 indicates the results of the PCA and Panel B in Table 3 the descriptive statistics of participants' single factor digital knowledge for the four groups.

Experimental design

The case is based on those developed by Dezoort *et al.* (2001) and Glover *et al.* (2008) and is presented in Appendix. The case contains four sections, providing information about a fictional organization and its IA department. As two conditions were manipulated (the use/non-use of data analytics and the performance/non-performance of consulting activities), four different versions were developed.

The case provided the general context of the experiment, including text stipulating that participants should assume the role of the CEO of a fictional organization. To ensure that the

Table 2.
Descriptive statistics
of the digital
knowledge scale

Digital knowledge items	No data analytics		Yes data analytics	
	No cons (N = 29)	Yes cons (N = 28)	No cons (N = 31)	Yes cons (N = 32)
<i>I consider myself knowledgeable about digital technologies</i>				
Mean	7.93	8.04	8.29	8.00
(SD)	(1.83)	(1.64)	(1.75)	(2.05)
<i>I am extremely skilled at using digital technologies</i>				
Mean	7.86	7.64	7.90	7.66
(SD)	(1.77)	(1.83)	(2.13)	(2.03)
<i>I know how to use digital technologies</i>				
Mean	8.21	8.25	8.61	8.19
(SD)	(1.50)	(1.88)	(1.63)	(1.93)
<i>I know somewhat more than my peers about digital technologies</i>				
Mean	7.62	7.68	8.06	7.50
(SD)	(1.88)	(1.87)	(1.88)	(2.20)
Source: Created by authors				

Table 3.
PCA results and
summary of
participants' single
factor digital
knowledge

	# of items	KMO index	Bartlett test	% explained variance	Cronbach's alpha
<i>Panel A: Results of the PCA</i>					
Digital knowledge of participants	4	0.839	Chi ² : 435.039 ddl: 6 p-value: 0.000**	83.736	0.933
<i>Panel B: Cell means – mean (std. dev.) [cell size]</i>					
	No data analytics			Yes data analytics	
No consulting	7.91	(1.57)	[29]	8.22	(1.69) [31]
Yes consulting	7.90	(1.59)	[28]	7.84	(1.94) [32]
Average	7.90	(1.57)	[57]	8.02	(1.82) [63]
Notes: *Significant at the 0.05 level (two-tailed); **significant at the 0.01 level (two-tailed)					
Source: Created by authors					

study participants were able to understand the implications of the CEO role within an organization, participants were recruited on Prolific by focusing on the platform's "Upper Management" and "Middle Management" profiles. The case also provided a description of the company, its industry and its business objectives. This section did not contain any manipulations and was the same across all four versions of the case.

The second section provided information about the role of the IA department. This was manipulated as either focused solely on assurance activities or dedicated to both assurance and consulting activities.

The third section detailed the work performed and tools used by the IA department. The first part of this section described the IA department's audit program. The last part of the section contained the manipulation and details of whether the IA department performed its work using sampling or full data sets. The term "analyses based on full data sets" was used instead of "data analytics" to avoid potential respondent bias related to the term "data analytics."

The last section included questions related to the four dimensions of the IA quality framework (input, process, output and outcome) as well as manipulation checks and demographic questions. This section was the same for all the cases. [Figure 3](#) summarizes the flow of the case.

Independent variables

The first manipulation involved the extent to which the IAF dedicated its time to consulting activities. Prior research ([Betti and Sarens, 2021](#)) finds that the IAF tends to perform either solely assurance-type work or either a mix of assurance-type and consulting-type works. This is consistent with the findings of prior research ([Brandon, 2010](#); [Soh and Martinov-Bennie, 2011](#);

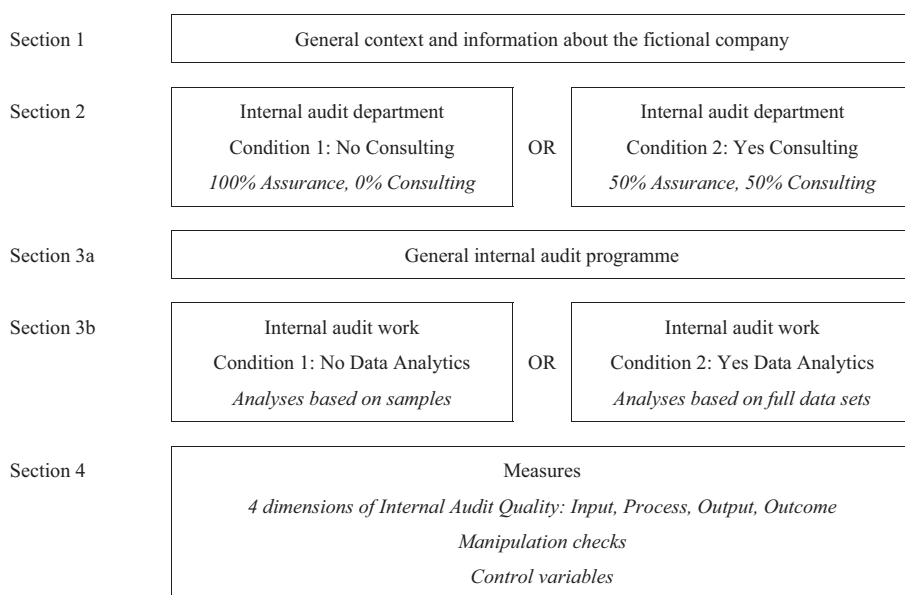


Figure 3.
Description of the procedure

Source: Created by authors

Stewart and Subramaniam, 2010) and manipulations used in prior IA research (Munro and Stewart, 2010, 2011; Stewart and Subramaniam, 2010). Additionally, practitioner publications consistently stress the importance of internal auditor engagement in consulting activities to stay relevant and add value to organizations (Fulton and Parchure, 2018; Jacka, 2016; Piper, 2016; Zwelling, 2019). Therefore, to increase the ecological validity of the study, the presented conditions of the first manipulation are in line with such practice. Both conditions of the manipulation (No Consulting/Yes Consulting) were presented as follows:

No Consulting condition: The case indicates that the internal audit department dedicates 100% of its time to assurance activities and does not perform any consulting activities for management such as improvement or development of processes, involvement in enterprise risk management or other consulting projects.

Yes Consulting condition: The case indicates that the internal audit department dedicates 50% of its time to assurance activities. In addition to assurance activities, the internal audit department dedicates 50% of its time to consulting activities for management such as improvement or development of processes, involvement in enterprise risk management or other consulting projects.

The second manipulation concerns the use of data analytics by internal auditors. Both conditions of the manipulation (No Data Analytics/Yes Data Analytics) were presented as follows:

No Data Analytics condition: The case stipulates that internal auditors perform analyses, testing and reviews based on samples. Once a sample is selected, internal auditors perform manual detailed checks for each selected item. Internal auditors also perform ratio and trend analyses comparing the audit period to prior periods.

Yes Data Analytics condition: The case stipulates that internal auditors perform analyses, testing and reviews of full data sets. Once a full data set is extracted, internal auditors use an application that enables a detailed check for all items. Internal auditors also use the application to predict future events by identifying potential trends or clusters, which enables users to perform simulations to suggest potential actions or recommendations.

Appendix provides the experimental materials.

Dependent variables

This study investigates the effects of the performance of consulting activities and the use of data analytics by internal auditors on IA quality as perceived by managers. Following Trotman and Duncan's (2018) framework, we assess perceived IA quality with four dimensions, namely, the input, the process, the output and the outcome [6]. All variables were measured on 11-point Likert scales (Brandon, 2010; Davidson *et al.*, 2013; Dezoort *et al.*, 2001; Glover *et al.*, 2008) and related to the whole case.

To assess the input dimension, we asked respondents to what extent they considered the IA department competent (Brandon, 2010; Davidson *et al.*, 2013; Glover *et al.*, 2008); and objective (Brandon, 2010; Davidson *et al.*, 2013; Glover *et al.*, 2008). For the question related to objectivity, we included the Institute of Internal Auditors (2017) Standards' definition, which states that objectivity is defined as an impartial and unbiased attitude to avoid conflicts of interest.

The process dimension was measured with questions based on Trotman and Duncan's (2018) framework. Specifically, questions asked about the likelihood that internal auditors

will develop an effective audit methodology; and develop strong working relationships with management. The following definition of an “effective” methodology was provided:

An effective methodology is defined as a rigorous methodology in the process and execution to support internal audit’s findings and recommendations but flexible enough to address all important risks and issues.

The third dependent variable addresses outputs. We asked questions related to the quality of the IAF reports, including accuracy and timeliness of the reports; and the ability of the IA department to provide relevant recommendations.

Finally, respondents were asked to provide their perception on the extent to which the IA department was likely to bring value to the company.

Manipulation checks

At the end of the fourth section, two questions were asked to assess participants’ understanding of our manipulations. The data analytics use manipulation was checked by asking: “on a scale from 0 to 10, please indicate to what extent the IA department performs analyses based on samples or analyses based on full data sets.” The consulting activities manipulation was checked by asking “on a scale from 0 to 10, please indicate to what extent the internal audit department performs consulting activities.”

Pretest procedure

We pretested the comprehensibility of the scenarios and checked manipulations with a sample of 41 executive master’s students in internal auditing who had completed at least one internship and PhD students in accountancy with significant work experience. Given that these students are specializing in the fields of internal auditing and accountancy, they were able to understand the given scenarios in the experiment (Mursita and Nahartyo, 2022; Trapp and Trapp, 2019). Following Mursita and Nahartyo (2022), we undertook three steps to avoid any bias with a sample of students. First, anonymity and confidentiality of the performance during the experiment were guaranteed to students to avoid the social desirability bias. Also, scenarios were randomized across participants to avoid selection bias. Finally, students were not informed of the purpose of the study to avoid the demand effect.

The results of the pre-test indicated that participants passed the consulting manipulation (mean no consulting = 2.90 [$N = 20$] versus mean yes consulting = 7.19 [$N = 21$]; $F = 3.213$; $p = 0.007$; two-tailed) and the data analytics manipulation (mean no data analytics = 6.45 [$N = 22$] versus mean yes data analytics = 8.53 [$N = 19$]; $F = 3.181$; $p = 0.008$; two-tailed). In addition, we had several discussions with internal auditors, managers and other researchers regarding our instrument. These discussions helped us improve the experimental design.

Results

Manipulation checks and inter-group equivalence

Manipulation checks show that our manipulations were successful. Participants passed the consulting manipulation (mean no consulting = 3.03 versus mean yes consulting = 7.38; $F = 52.084$; $p = 0.000$; two-tailed), as well as the data analytics manipulation (mean no data analytics = 6.25 versus mean yes data analytics = 8.54; $F = 19.892$; $p = 0.000$; two-tailed). We also controlled the equivalence of randomized participant assignment to conditions in terms of knowledge of digital technologies, experience as measured by years in current job and gender. The results indicate that the four groups were equivalent in terms of knowledge of digital technologies ($F = 0.311$; $p = 0.818$; two-tailed), experience in current job role

JAOC

($F = 1.047$; $p = 0.375$; two-tailed) and gender ($F = 0.830$; $p = 0.480$; two-tailed). Panel A in [Tables 4](#) and [5](#) present the descriptive statistics of the manipulations, while Panel B in these tables shows the results of the manipulation check tests. [Table 6](#) shows the equivalence tests between the four groups.

Test of hypotheses

[Table 7](#) shows the means and standard deviations of respondents' assessments of the quality variables by condition.

To test the hypotheses, we ran general linear models with consulting activities and data analytics as factors [\[7\]](#). [Table 8](#) presents the results of the general linear models for each of the seven variables.

		No data analytics			Yes data analytics			Average		
<i>Panel A: Cell means – mean (std. dev.) [cell size]</i>										
No consulting		2.17	(3.23)	[29]	3.84	(4.23)	[31]	3.03	(3.84)	[60]
Yes consulting		7.11	(2.57)	[28]	7.63	(2.74)	[32]	7.38	(2.66)	[60]
<i>Panel B: ANOVA results</i>										
Source		Sum of squares		Df	Mean square		F-ratio		<i>p</i> -value (two-tailed)	
Consulting		567.675		1	567.675		52.084		0.000***	
Note: ***Significant at the 0.01 level (one-tailed)										
Source: Created by authors										

Table 4.
Test of consulting manipulation check

Table 4.
Test of consulting
manipulation check

		No consulting			Yes consulting			Average		
<i>Panel A: Cell means – mean (std. dev.) [cell size]</i>										
No data analytics		6.55	(3.47)	[29]	5.93	(3.71)	[28]	6.25	(3.57)	[57]
Yes data analytics		8.48	(1.75)	[31]	8.59	(2.03)	[32]	8.54	(1.88)	[63]
<i>Panel B: ANOVA results</i>										
Source		Sum of squares		Df	Mean square		F-ratio		<i>p</i> -value (two-tailed)	
Data Analytics		157.488		1	157.488		19.892		0.000***	
Table 5. Test of data analytics manipulation check		Note: ***Significant at the 0.01 level (one-tailed)								
		Source: Created by authors								

Table 5.
Test of data analytics
manipulation check

ANOVA results					
Source	Sum of squares	Df	Mean square	F-ratio	<i>p</i> -value (two-tailed)
Digital knowledge	2.729	3	0.910	0.311	0.818
Years in the current job	55.234	3	18.411	1.047	0.375
Gender	0.601	3	0.200	0.830	0.480
Source: Created by authors					

Table 6.
Test of equivalence
between groups

Quality dimension and description*	No data analytics		Yes data analytics		Use of data analytics	
	No cons (N = 29)	Yes cons (N = 28)	No cons (N = 31)	Yes cons (N = 32)		
<i>Input:</i> The IA department is competent						
Mean	8.21	8.25	8.68	8.84		
(SD)	(1.54)	(1.69)	(1.33)	(1.35)		
<i>Input:</i> The IA department is objective						
Mean	7.24	7.11	7.39	7.28		
(SD)	(1.81)	(2.56)	(1.73)	(2.53)		
<i>Process:</i> The IA department has an effective audit methodology						
Mean	7.90	8.04	8.19	8.34		
(SD)	(1.63)	(2.19)	(1.78)	(1.82)		
<i>Process:</i> The IA department is likely to develop strong working relationships with management						
Mean	7.10	6.96	6.32	8.09		
(SD)	(2.30)	(2.66)	(2.52)	(1.96)		
<i>Output:</i> The IA department is likely to provide accurate and timely reports						
Mean	8.34	8.61	8.48	8.72		
(SD)	(1.37)	(1.17)	(1.71)	(1.73)		
<i>Output:</i> The IA department is likely to provide relevant recommendations						
Mean	8.00	8.36	7.77	8.88		
(SD)	(1.77)	(1.22)	(2.33)	(1.24)		
<i>Outcome:</i> The IA department is likely to bring value to the company						
Mean	8.38	8.29	8.55	8.56		
(SD)	(1.32)	(1.74)	(1.36)	(1.61)		
Note: *All variables were measured on 11-point scales					Table 7. Descriptive statistics	
Source: Created by authors						

H1 results indicate that the perceived competency of internal auditors was significantly higher when IAFs use data analytics than when they do not use data analytics (means: 8.76 versus 8.23; $F(1;116) = 3.884$; $p = 0.051$; two-tailed). However, results do not indicate any significant main effect of the use of data analytics on other variables of the IA quality framework. Thus, *H1* is supported regarding the input dimension.

Regarding *H2*, results suggest that the perceived quality of the relationship between the IAF and management is higher when internal auditors perform consulting activities than when they do not perform consulting activities (means: 7.57 versus 6.70; $F(1;116) = 3.560$; $p = 0.062$; two-tailed). Results also indicate that perceived relevance of internal auditors' recommendations is higher when internal auditors perform consulting activities (means: 8.63 versus 7.88; $F(1;116) = 5.434$; $p = 0.021$; two-tailed). However, the results do not indicate a significant main effect of the performance of consulting activities on other variables of the IA quality framework. Thus, *H2* is supported regarding the process and the output dimensions. The results also suggest no significant difference regarding the level of objectivity of the IA department whether the IAF performs consulting activities or not (means: 7.20 versus 7.32; $F(1;116) = 0.90$; $p = 0.765$).

Concerning *H3*, results show a significant interaction effect between the performance of consulting activities and the use of data analytics on the perceived quality of the relationship between internal auditors and management ($F(1;116) = 4.877$; $p = 0.029$; two-tailed). When internal auditors jointly perform data analytics and consulting activities, managers' perceived quality of the relationship between the IAF and management

Variable	Df	Mean square	F-ratio	p-value (two-tailed)
<i>Competence of the IAF (input dimension)</i>				
Consulting	1	0.328	0.150	0.699
Data analytics	1	8.471	3.884	0.051*
Consulting * Data analytics	1	0.114	0.052	0.820
<i>Objectivity of the IAF (input dimension)</i>				
Consulting	1	0.431	0.090	0.765
Data analytics	1	0.765	0.160	0.690
Consulting * Data analytics	1	0.006	0.001	0.972
<i>Effective methodology of the IAF (process dimension)</i>				
Consulting	1	0.626	0.181	0.671
Data analytics	1	2.738	0.791	0.376
Consulting * Data analytics	1	0.001	0.000	0.987
<i>Relationship of the IAF with management (process dimension)</i>				
Consulting	1	19.920	3.560	0.062*
Data analytics	1	0.909	0.162	0.688
Consulting * Data analytics	1	27.294	4.877	0.029**
<i>Accuracy of the IAF's reports (output dimension)</i>				
Consulting	1	1.849	0.796	0.374
Data analytics	1	0.470	0.202	0.654
Consulting * Data analytics	1	0.006	0.002	0.961
<i>Relevance of IAF's recommendations (output dimension)</i>				
Consulting	1	15.898	5.434	0.021**
Data analytics	1	0.638	0.218	0.641
Consulting * Data analytics	1	4.136	1.414	0.237
<i>Added value of the IAF (outcome dimension)</i>				
Consulting	1	0.047	0.021	0.886
Data analytics	1	1.487	0.648	0.422
Consulting * Data analytics	1	0.087	0.038	0.846

Table 8.
Test of hypotheses

Notes: *Significant at the 0.10 level (one-tailed); **significant at the 0.05 level (one-tailed)
Source: Created by authors

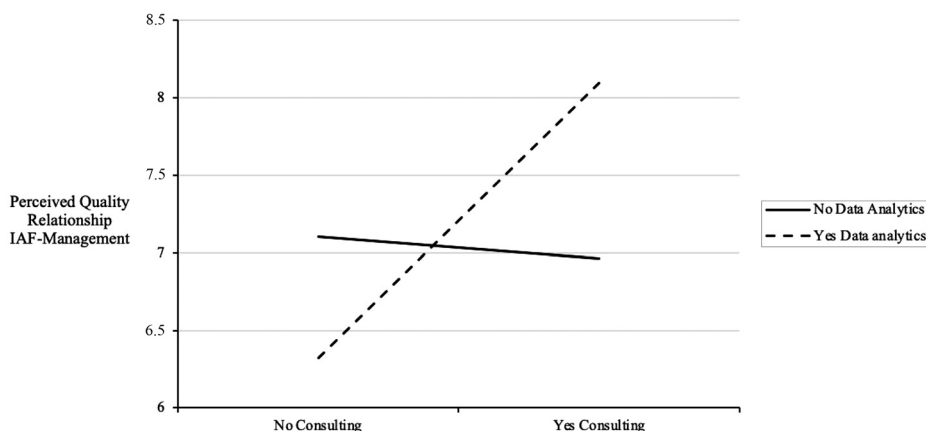
increased. Figure 4 plots this interaction. This result supports *H3* regarding the process dimension. However, results do not show other significant interaction effects between these two variables on other dimensions of the internal quality framework.

In summary, *H1* is supported regarding the input dimension of the IA quality framework; *H2* is supported regarding the process and the output dimensions; and *H3* is supported regarding the process dimension.

Discussion and conclusion

This research investigates the effect of the use of data analytics and the performance of consulting activities on managers' perceptions of audit quality. We demonstrate that the use of data analytics and the performance of consulting activities improve some dimensions of perceived IA quality. Our findings show that the use of data analytics enhances the input dimension of the IA quality framework, while the performance of consulting activities enhances the process and output dimensions. Finally, results also indicate that the combination of the performance of consulting activities and the use of data analytics strengthens the effect on the process dimension. The hypotheses and their results are summarized below, in Table 9.

Use of data analytics



Source: Created by authors

Figure 4.
Interaction effect of consulting and data analytics on the perceived quality of the relationship between internal auditors and management

Hypotheses	Results
<i>H1:</i> Perceived IA quality will be higher when internal auditors use data analytics than when internal auditors do not use data analytics	Supported for input
<i>H2:</i> Perceived IA quality will be higher when internal auditors perform consulting activities than when internal auditors do not perform consulting activities	Supported for process Supported for output
<i>H3:</i> When internal auditors perform consulting activities, perceived IA quality will be higher when internal auditors use data analytics than when internal auditors do not use data analytics	Supported for process

Source: Created by authors

Table 9.
Summary of the results

Examining first the use of data analytics, our findings indicate that managers perceive the IAF as more competent (input dimension) when it uses data analytics to accomplish its mission. This is likely because data analytics enable the IAF to carry out more targeted and in-depth analyses (Christ *et al.*, 2019; ECIA, 2019; Islam and Stafford, 2022; Protiviti, 2018) and to make more precise assessments that facilitate the organizational decision-making process (Al-Htaybat and von Alberti-Alhtaybat, 2017; Betti and Sarens, 2021). However, the use of data analytics does not seem to directly impact the objectivity aspect of the input dimension as well as the other dimensions of perceived IA quality, namely, process, output and outcome. First, managers do not perceive that data analytics impacts the process dimension, which refers to the effectiveness of the methodology and to service interactions. Nevertheless, we did observe an interaction effect as discussed below. Second, contrary to expectations, we observe that the use of data analytics is perceived to affect neither the quality of IAF reports nor the perceived relevance of IAF recommendations (output dimension). However, we acknowledge that internal auditor outputs do not come exclusively from the data; they also derive from the auditors' interpretation of that data, which may explain the lack of findings. Finally, we also expected an increase in perceived added value (outcome dimensions) when internal auditors use data analytics, but our results do not support this. Our findings that no effect of data analytics was identified on the process,

output and outcome dimensions is surprising given that the literature suggests that data analytics enable advanced analyses not only on past events but also on future events by using predictive analyses (Al-Htaybat and von Albeti-Alhtaybat, 2017; Islam and Stafford, 2022). The lack of findings on these dimensions may be explained by the fact that the use of data analytics is still not standard in many IAFs (Betti *et al.*, 2021; Islam and Stafford, 2022), which could lead to respondents in the “no data analytics” condition not recognizing that data analytics were missing from the internal auditors work. Recent reports (Institute of Internal Auditors, 2018, 2019) highlight that the use of data analytics is still limited and is not implemented in an advanced way inside IA departments.

When examining the performance of consulting activities, our results show that managers perceive the quality of their relationship with internal auditors as higher when internal auditors perform consulting activities (process dimension). This is consistent with prior research indicating that consulting activities bring value to organizations (Betti and Sarens, 2021; Castanheira *et al.*, 2010; Chapman, 2001; Lenz and Hoos, 2023; Soh and Martinov-Bennie, 2011; Stewart and Subramaniam, 2010; Volodina *et al.*, 2022). Managers increasingly expect the IAF to become more a business partner who supports them on strategic risks and initiatives (Betti *et al.*, 2021). Furthermore, when internal auditors perform consulting activities, the perceived quality of their recommendations was higher (output dimension). This may be because internal auditors that perform consulting activities better understand auditees’ challenges and are therefore in a better position to provide more relevant recommendations. Additionally, it is interesting to note that the performance of consulting activities did not affect the perceived objectivity of auditors from the managers’ point of view in this study (input dimension). This contradicts prior research indicating that consulting activities jeopardize the objectivity of internal auditors (i.e. Lenz and Hahn, 2015; Roussy, 2013; Soh and Martinov-Bennie, 2011). However, our findings indicate no impact of consulting on the other parts of the quality framework, namely, the competence of internal auditors (input dimension), the effectiveness of the methodology (process dimension), the quality of the reports (output dimension) and the perceived added value of the IAF (outcome dimension). This last result is surprising given that prior research indicates that consulting activities are considered as value-adding activities (i.e. Betti and Sarens, 2021; Soh and Martinov-Bennie, 2015; Stewart and Subramaniam, 2010) and are considered as a way for the IAF to be closer to strategic risks and to be more involved in enterprise risk management (Allegrini *et al.*, 2011; Stewart and Subramaniam, 2010).

We also hypothesized that when internal auditors perform consulting activities, perceived IA quality would be higher with use of data analytics than without. We did observe this effect for the process dimension, specifically concerning the perceived quality of the relationship between internal auditors and management. When internal auditors perform consulting activities with the use of data analytics, internal auditors were perceived to have a better working relationship with management. This may be because digital knowledge is gaining importance in organizations (Betti and Sarens, 2021; Islam and Stafford, 2022) and that performance of consulting activities by internal auditors is well perceived by management (Betti and Sarens, 2021; Betti *et al.*, 2021; Ege *et al.*, 2022). Combining these two attributes could be seen as an asset by management, thus increasing the likelihood of a strong working relationship.

Theoretical implications

From a theoretical perspective, our contributions to the IA literature are fivefold. First, we assess perceived IA quality holistically by testing Trotman and Duncan’s (2018) framework through an experiment. Prior research has mainly assessed perceived IA quality based on

the input dimension (i.e. [Brandon, 2010](#); [Davidson et al., 2013](#); [Glover et al., 2008](#)). This prior research used proxies to assess the quality of an IA department relying on the assessment of perceived competence and objectivity of the IAF. Using the entire framework developed by [Trotman and Duncan \(2018\)](#) enabled us to assess IA quality in four dimensions: input, process, output and outcome and on distinct elements within each dimension.

Second, [Trotman and Duncan \(2018\)](#) identified contextual factors as an important variable influencing the IA quality. [Betti et al. \(2021\)](#) called for research on the effect of using digital technologies on the perceived IA quality. This research responds to these calls by specifically examining the effect of digitalization, in the form of data analytics, on the IAF quality, building on [Trotman and Duncan's \(2018\)](#) framework. We demonstrate that the use of data analytics impacts perceived IA quality, specifically the input dimension. Managers perceive the IAF as more competent when it uses data analytics to accomplish its mission.

Third, [Trotman and Duncan \(2018\)](#) and [Betti et al. \(2021\)](#) called for future research on the impact of the nature of the engagement (consulting and assurance), a key contextual factor, on IA quality. In this research, we show that performing consulting activities enhances managers' perceptions of IA quality, specifically the process and the output dimensions. Managers perceive that the quality of their relationship with the IAF (process dimension) and of the recommendations made by the IAF (output dimensions) are better when the IAF performs consulting activities

Fourth, the assessment of IA quality varies depending on the IAF's major stakeholders ([Oussii and Boulila Taktak, 2018](#); [Trotman and Duncan, 2018](#)). We had limited knowledge about how the performance of consulting activities and the use of data analytics influence the perceived IA quality, especially by stakeholders others than external auditors ([Trotman and Duncan, 2018](#)). This research extends [Trotman and Duncan's \(2018\)](#) work by improving understanding of perceived IA quality among managers, a key stakeholder of the IAF.

Finally, some dimensions of the qualitative framework of [Trotman and Duncan \(2018\)](#); specifically process, output and outcome, had not been tested before. We were therefore not able to use measures developed in prior research. As a result, we developed new measures for these three dimensions of the IA quality framework.

Managerial implications

From a managerial point of view, this research shows that the use of data analytics, especially combined with the performance of consulting activities, improves managers' perceptions of IA quality. This is likely because the use of data analytics can help the IAF manage the complexity of engagement ([Betti and Sarens, 2021](#)). This technology enables auditors to perform more advanced analyses on full population but also to work on data from multiple sources ([Betti and Sarens, 2021](#); [Islam and Stafford, 2022](#); [Manita et al., 2020](#); [Protiviti, 2018](#)). Thus, internal auditors may want to consider increasing their use of data analytics. This first raises the question of how the IAF can develop such skills inside IA departments. We posit that IA departments can improve their data analytics expertise through training existing employees as well as recruiting those with data analytics expertise. It also raises the question whether all internal auditors within a particular department should possess data analytics skills or whether IA departments should have only some internal auditors specializing in data analytics. In addition, our results suggest that internal auditors can also increase the proportion of the audit plan dedicated to consulting activities to strengthen the relationship with management. The recently updated three lines model highlights the importance of this relationship for the IAF to be closer to strategic risks ([Institute of Internal Auditors, 2020](#)).

Limitations and future research

This research investigated the effect of the use of data analytics and the performance of consulting activities on managers' perceptions of IA quality. Our results should be interpreted with caution due to limitations of the current research, but also presents opportunities for future research.

The perception of IA quality varies depending on the stakeholder (Oussii and Boulila Taktak, 2018; Trotman and Duncan, 2018), who tend to emphasize some dimensions depending on the lens through which they form their judgment (Trotman and Duncan, 2018). This research focused on the perceptions of only one IA stakeholder: managers. One potential direction for future research could be to examine the perceptions of other IAF stakeholders such as external auditors and/or internal auditors. Prior research suggests, for instance, that the more involved an IAF is in operational activities such as consulting, the less objective the IAF is perceived to be by external auditors, thus leading to a low-quality assessment (Glover *et al.*, 2008; Gramling and Myers, 2006; Gramling *et al.*, 2004; Prawitt *et al.*, 2009). Therefore, for external auditors, this suggests that consultancy activities by IAFs may lead to a decrease in perceived quality. Future studies could therefore investigate whether the use of data analytics, which facilitates a more fact-based analysis, may mitigate the possible negative effect of the performance of consulting activities on external auditors' perceptions of IA quality. Future research could also investigate to what extent IA departments should engage in data analytics by considering whether IAFs should have only a few data analytics specialists inside the department or whether every internal auditor in the IAF should have these skills.

Furthermore, the scenario we used to conduct the experiment presents an organization in a non-financial sector. Future research should investigate the perceptions of the IAF quality for organizations in the financial sector, that tends to be more regulated (Gras-Gil *et al.*, 2012; Koutoupis and Tsamis, 2009; Naheem, 2016). Finally, our participants came from only one country, the USA, and their perceptions may not be generalizable to other regions. Our knowledge of what factors effect perceived IAF quality may benefit from analyzing other countries/regions. Such studies will require an analysis of cultural dimensions, legal/regulatory characteristics and other variables in various countries.

Despite these limitations our study contributes significantly to the literature by further examining the factors and context that influence management's perception of IA quality. Future research can examine this relationship in more depth, the perceptions of other stakeholders, and can examine IA quality perceptions in other contexts.

Notes

1. In this paper, data analytics is considered an application of digitalization inside organizations (Betti and Sarens, 2021; Betti *et al.*, 2021).
2. The technical audit production indicators are the methodology used within the audit, auditing in alignment with the organizational perspective, and the audit approach. Under the service interaction area, the two quality indicators are strong relationships among stakeholders and the engagement closeout procedures.
3. Following the IIA's (2017, p. 3) definition, we consider an IAF as independent if it is "free from conditions that threaten the ability of the internal audit activity to carry out internal audit responsibilities in an unbiased manner." An IAF and its members are objective if they possess an "unbiased mental attitude that allows them to perform engagements in such a manner that they believe in their work product and that no quality compromises are made" (IIA, 2017, p. 4).

4. Fewer than one third of chief audit executives surveyed reported that their groups extensively used the simplest data analytics techniques (IIA, 2018). 63% of IAFs surveyed used data analytics as part of the audit process (Protiviti, 2018).
5. www.prolific.co/
6. Although Trotman and Duncan (2018) find that the outcome dimension is the primary focus of management, we tested all dimensions of their framework to extend their work.
7. We also ran tests using organization type (listed versus non-listed) as a control and the results remained unchanged.

References

- Abdelrahim, A. and Al-Malkawi, H.-A.N. (2022), "The influential factors of internal audit effectiveness: a conceptual model", *International Journal of Financial Studies*, Vol. 10 No. 3, pp. 1-23, doi: [10.3390/ijfs10030071](https://doi.org/10.3390/ijfs10030071).
- Al-Htaybat, K. and von Alberti-Alhtaybat, L. (2017), "Big data and corporate reporting: impacts and paradoxes", *Accounting, Auditing and Accountability Journal*, Vol. 30 No. 4, pp. 850-873, doi: [10.1108/AAAJ-07-2015-2139](https://doi.org/10.1108/AAAJ-07-2015-2139).
- Allegrini, M., D'Onza, G., Melville, R., Sarens, G. and Selim, G.M. (2011), "The IIA's global internal audit survey: a component of the CBOK study. What's next for internal auditing?", available at: <https://na.theiia.org/iia/rf/Public%20Documents/Whats-Next-for-Internal-Auditing.pdf> (accessed 30 September 2020).
- American Institute of Certified Public Accountants (AICPA) (2017), "Audit data analytics (ADAs) can transform audits; new AICPA guide will help auditors apply ADA techniques", available at: www.aicpa.org/press/pressreleases/2017/audit-data-analytics-new-aicpa-guide-will-help-auditors-apply-ada-techniques.html (accessed 7 August 2020).
- Bame-Aldred, C.W., Brandon, D.M., Messier, W.F., Jr, Rittenberg, L.E. and Stefaniak, C.M. (2013), "A summary of research on external auditor reliance on the internal audit function", *Auditing: A Journal of Practice and Theory*, Vol. 32, pp. 251-286, doi: [10.2308/ajpt-50342](https://doi.org/10.2308/ajpt-50342).
- Bartley, K. (2022), "Big data statistics: how much data is there in the world?", Riverty.com, available at: <https://riverty.io/blog/big-data-statistics-how-much-data-is-there-in-the-world/> (accessed 20 December 2022).
- Betti, N. and Sarens, G. (2021), "Understanding the internal audit function in a digitalised business environment", *Journal of Accounting and Organizational Change*, Vol. 17 No. 2, pp. 197-216, doi: [10.1108/JAOC-11-2019-0114](https://doi.org/10.1108/JAOC-11-2019-0114).
- Betti, N., Sarens, G. and Poncin, I. (2021), "Effects of digitalization of organizations on internal audit activities and practices", *Managerial Auditing Journal*, Vol. 36 No. 6, pp. 872-888, doi: [10.1108/MAJ-08-2020-2792](https://doi.org/10.1108/MAJ-08-2020-2792).
- Bouwman, H., Nikou, S., Molina-Castillo, F.J. and de Reuver, M. (2018), "The impact of digitalization on business models", *Digital Policy, Regulation and Governance*, Vol. 20 No. 2, pp. 105-124, doi: [10.1108/DPRG-07-2017-0039](https://doi.org/10.1108/DPRG-07-2017-0039).
- Brandon, D.M. (2010), "External auditor evaluations of outsourced internal auditors", *Auditing: A Journal of Practice and Theory*, Vol. 29 No. 2, pp. 159-173, doi: [10.2308/aud.2010.29.2.159](https://doi.org/10.2308/aud.2010.29.2.159).
- Brody, R.G. and Lowe, D.J. (2000), "The new role of the internal auditor: implications for internal auditor objectivity", *International Journal of Auditing*, Vol. 4 No. 2, pp. 169-176, doi: [10.1111/1099-1123.00311](https://doi.org/10.1111/1099-1123.00311).
- Brown, T. and Fanning, K. (2019), "The joint effects of internal auditors' approach and persuasion tactics on managers' responses to internal audit advice", *The Accounting Review*, Vol. 94 No. 4, pp. 173-188, doi: [10.2308/accr-52295](https://doi.org/10.2308/accr-52295).

- Canning, M., Gendron, Y. and O'Dwyer, B. (2018), "Auditing in a changing environment and the constitution of cross-paradigmatic communication channels", *Auditing: A Journal of Practice and Theory*, Vol. 37 No. 2, pp. 165-174, doi: [10.2308/ajpt-10577](https://doi.org/10.2308/ajpt-10577).
- Cashell, J.D. and Aldhizer, G.R. (2002), "An examination of internal auditors' emphasis on value-added services", *Internal Auditing*, Vol. 17 No. 5, pp. 19-31.
- Castanheira, N., Rodriguez, L.L. and Craig, R. (2010), "Factors associated with the adoption of risk-based internal auditing", *Managerial Auditing Journal*, Vol. 25 No. 1, pp. 79-98, doi: [10.1108/02686901011007315](https://doi.org/10.1108/02686901011007315).
- Chapman, C. (2001), "Raising the bar", *Internal Auditor*, Vol. 58 No. 2, pp. 55-59.
- Christ, M.H., Eulrich, M. and Wood, D.A. (2019), "Internal auditors' response to disruptive innovation", available at: www.incp.org.co/wp-content/uploads/2019/06/Internal-Auditors-Response-to-Disruptive-Innovation-13062019.pdf (accessed 7 August 2020).
- Cohen, J.R., Hayes, C., Krishnamoorthy, G., Monroe, G.S. and Wright, A. (2013), "The effectiveness of SOX regulation: an interview study of corporate directors", *Behavioral Research in Accounting*, Vol. 25 No. 1, pp. 61-87, doi: [10.2308/bria-50245](https://doi.org/10.2308/bria-50245).
- Cohen, J., Krishnamoorthy, G. and Wright, A. (2004), "The corporate governance mosaic and financial reporting quality", *Journal of Accounting Literature*, Vol. 23 No. 1, pp. 87-152.
- D'Onza, G., Lamboglia, R. and Verona, R. (2015), "Do IT audits satisfy senior manager expectations? A qualitative study based on Italian banks", *Managerial Auditing Journal*, Vol. 30 Nos 4/5, pp. 413-434, doi: [10.1108/MAJ-07-2014-1051](https://doi.org/10.1108/MAJ-07-2014-1051).
- Davidson, B.I., Desai, N.K. and Gerard, G.J. (2013), "The effect of continuous auditing on the relationship between internal audit sourcing and the external auditor's reliance on the internal audit function", *Journal of Information Systems*, Vol. 27 No. 1, pp. 41-59, doi: [10.2308/isys-50430](https://doi.org/10.2308/isys-50430).
- Dezort, F.T., Houston, R.W. and Peters, M.F. (2001), "The impact of internal auditor compensation and role on external auditors' planning judgments and decisions", *Contemporary Accounting Research*, Vol. 18 No. 2, pp. 257-281, doi: [10.1506/7ERQ-LD54-BTQV-TUVE](https://doi.org/10.1506/7ERQ-LD54-BTQV-TUVE).
- Dixon, G. and Singer, S. (2011), "Unlocking the strategic value of internal audit: three steps to transformation", *Internal Auditing*, Vol. 26 No. 3, pp. 9-18, available at: https://i.forbesimg.com/forbesinsights/StudyPDFs/Unlocking_Strategic_ValueofInternal_Audit.pdf (accessed 22 December 2021).
- Earley, C.E. (2015), "Data analytics in auditing: opportunities and challenges", *Business Horizons*, Vol. 58 No. 5, pp. 493-500, doi: [10.1016/j.bushor.2015.05.002](https://doi.org/10.1016/j.bushor.2015.05.002).
- Ege, M.S. (2015), "Does internal audit function quality deter management misconduct?", *The Accounting Review*, Vol. 90 No. 2, pp. 495-527, doi: [10.2308/accr-50871](https://doi.org/10.2308/accr-50871).
- Ege, M., Seidel, T.A., Sterin, M. and Wood, D.A. (2022), "The influence of management's internal audit experience on earnings management", *Contemporary Accounting Research*, Vol. 39 No. 3, pp. 1834-1870, doi: [10.1111/1911-3846.12770](https://doi.org/10.1111/1911-3846.12770).
- Erasmus, L. and Coetzee, P. (2018), "Drivers of stakeholders' view of internal audit effectiveness: management versus audit committee", *Managerial Auditing Journal*, Vol. 33 No. 1, pp. 90-114, doi: [10.1108/MAJ-05-2017-1558](https://doi.org/10.1108/MAJ-05-2017-1558).
- European Confederation of Institutes of Internal Auditing (ECIIA) (2019), "Risk in focus 2019: hot topics for internal auditors", available at: www.eciia.eu/wp-content/uploads/2019/02/Risk-in-Focus_2019.pdf (accessed 7 September 2020).
- EY and Forbes (2017), "Data and analytics: high stakes, high rewards", available at: www.forbes.com/forbesinsights/ey_data_analytics_2017/ (accessed 7 August 2020).
- Farkas, M., Hirsch, R. and Kokina, J. (2019), "Internal auditor communications: an experimental investigation of managerial perceptions", *Managerial Auditing Journal*, Vol. 34 No. 4, pp. 458-481, doi: [10.1108/MAJ-06-2018-1910](https://doi.org/10.1108/MAJ-06-2018-1910).

-
- Flora, P.E. and Rai, S. (2015), "Navigating technology's top 10 risks: internal audit's role", available at: www.iaa.nl/SiteFiles/Publicaties/Navigating%20Technology%27s%20Top%2010%20Risks%20_Small.pdf (accessed 7 August 2020).
- Fulton, D. and Parchure, N. (2018), "Implementing a shared services model", *Internal Auditor*, The Institute of Internal Auditors, available at: <https://go.gale.com/ps/i.do?id=GALE%7CA529516680&sid=googleScholar&v=2.1&it=r&linkaccess=abs&issn=00205745&p=AONE&sw=w&userGroupName=anon%7Ecb0bde6d> (accessed 22 December 2021).
- Gandomi, A. and Haider, M. (2015), "Beyond the hype: big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35 No. 2, pp. 137-144, doi: [10.1016/j.ijinfomgt.2014.10.007](https://doi.org/10.1016/j.ijinfomgt.2014.10.007).
- Garven, S. and Scarlata, A. (2020), "An examination of factors associated with investment in internal auditing technology", *Managerial Auditing Journal*, Vol. 35 No. 7, pp. 955-978, doi: [10.1108/MAJ-06-2019-2321](https://doi.org/10.1108/MAJ-06-2019-2321).
- Glover, S.M., Prawitt, D.F. and Wood, D.A. (2008), "Internal audit sourcing arrangement and the external auditor's reliance decision", *Contemporary Accounting Research*, Vol. 25 No. 1, pp. 193-213, doi: [10.1506/car.25.1.7](https://doi.org/10.1506/car.25.1.7).
- Goodman, J.K., Cryder, C.E. and Cheema, A. (2013), "Data collection in a flat world: the strengths and weaknesses of mechanical Turk samples", *Journal of Behavioral Decision Making*, Vol. 26 No. 3, pp. 213-224, doi: [10.1002/bdm.1753](https://doi.org/10.1002/bdm.1753).
- Gramling, A.A. and Myers, P.M. (2006), "Internal auditing's role in ERM", *Internal Auditor*, Vol. 63 No. 2, pp. 52-58, available at: <https://digitalcommons.kennesaw.edu/facpubs/1326/> (accessed 22 December 2021).
- Gramling, A.A., Maletta, M.J., Schneider, A. and Church, B.K. (2004), "The role of the internal audit function in corporate governance: a synthesis of the extant internal auditing literature and directions for future research", *Journal of Accounting Literature*, Vol. 23, pp. 194-244.
- Gras-Gil, E., Marin-Hernandez, S. and Garcia-Perez de Lema, D. (2012), "Internal audit and financial reporting in the Spanish banking industry", *Managerial Auditing Journal*, Vol. 27 No. 8, pp. 728-753, doi: [10.1108/02686901211257028](https://doi.org/10.1108/02686901211257028).
- Institute of Internal Auditors (2017), "International standards for the professional practice of internal auditing (standards)", available at: <https://na.theiia.org/standards-guidance/Public%20Documents/IPPF-Standards-2017.pdf> (accessed 7 September 2020).
- Institute of Internal Auditors (2018), "North American pulse of internal audit: the internal audit transformation imperative", available at: <https://iiaghana.com.gh/globalassets/documents/pulse/2018-na-pulse-of-internal-audit-the-internal-audit-transformation-imperative.pdf> (accessed 7 September 2020).
- Institute of Internal Auditors (2019), "North American pulse of internal audit: defining alignment in a dynamic risk landscape", available at: www.theiia.org/globalassets/documents/aec-member-documents/2019-north-american-pulse-of-internal-audit.pdf (accessed 7 September 2020).
- Institute of Internal Auditors (2020), "The IIA's three lines model. An update of the three lines of defense", available at: www.theiia.org/globalassets/documents/resources/the-ias-three-lines-model-an-update-of-the-three-lines-of-defense-july-2020/three-lines-model-updated-english.pdf (accessed 7 September 2020).
- International Auditing and Assurance Standards Board (IAASB) (2014), "A framework for audit quality: key elements that create an environment for audit quality", available at: www.ifac.org/system/files/publications/files/A-Framework-for-Audit-Quality-Key-Elements-that-Create-an-Environment-for-Audit-Quality-2.pdf (accessed 7 August 2020).
- International Data Corporation (IDC) (2018), "Data age 2025. The digitization of the world. From edge to core", available at: www.seagate.com/files/www-content/our-story/trends/files/idc-seagate-dataage-whitepaper.pdf (accessed 7 September 2020).
- Islam, S. and Stafford, T. (2022), "Factors associated with the adoption of data analytics by internal audit function", *Managerial Auditing Journal*, Vol. 37 No. 2, pp. 193-223, doi: [10.1108/MAJ-04-2021-3090](https://doi.org/10.1108/MAJ-04-2021-3090).
-

- Jacka, M. (2016), "The perversion of value", *Internal Auditor*, The Institute of Internal Auditors, available at <https://go.gale.com/ps/i.do?id=GALE%7CA455416340&sid=googleScholar&v=2.1&it=r&linkaccess=abs&issn=00205745&p=AONE&sw=w&userGroupName=anon%7E4896eac8>
- Jones, K.K., Baskerville, R.L., Sriram, R.S. and Ramesh, B. (2017), "The impact of legislation on the internal audit function", *Journal of Accounting and Organizational Change*, Vol. 13 No. 4, pp. 450-470, doi: [10.1108/JAOC-02-2015-0019](https://doi.org/10.1108/JAOC-02-2015-0019).
- Kahyaoglu, S.B. and Caliyurt, K. (2018), "Cyber security assurance process from the internal audit perspective", *Managerial Auditing Journal*, Vol. 33 No. 4, pp. 360-376, doi: [10.1108/MAJ-02-2018-1804](https://doi.org/10.1108/MAJ-02-2018-1804).
- Kane, G.C., Palmer, D., Nguyen Phillips, A., Kiron, D. and Buckley, N. (2016), "Aligning the organization for its digital future", *MIT Sloan Management Review*, Vol. 58 No. 1, pp. 1-27.
- Knechel, W.R., Krishnan, G.V., Pevzner, M., Shefchik, L.B. and Velury, U.K. (2013), "Audit quality: insights from the academic literature", *AUDITING: A Journal of Practice and Theory*, Vol. 32, pp. 385-421, doi: [10.2308/ajpt-50350](https://doi.org/10.2308/ajpt-50350).
- Kokina, J. and Blanchette, S. (2019), "Early evidence of digital labor in accounting: innovation with robotic process automation", *International Journal of Accounting Information Systems*, Vol. 35, doi: [10.1016/j.accinf.2019.100431](https://doi.org/10.1016/j.accinf.2019.100431).
- Koreff, J., Weisner, M. and Sutton, S.G. (2021), "Data analytics (ab) use in healthcare fraud audits", *International Journal of Accounting Information Systems*, Vol. 42, p. 100523, doi: [10.1016/j.accinf.2021.100523](https://doi.org/10.1016/j.accinf.2021.100523).
- Koutoupis, A.G. and Tsamis, A. (2009), "Risk based internal auditing within Greek banks: a case study approach", *Journal of Management and Governance*, Vol. Vol. 13 Nos 1/2, pp. 101-130.
- Krieger, F., Drews, P. and Velte, P. (2021), "Explaining the (non-) adoption of advanced data analytics in auditing: a process theory", *International Journal of Accounting Information Systems*, Vol. 41, p. 100511, doi: [10.1016/j.accinf.2021.100511](https://doi.org/10.1016/j.accinf.2021.100511).
- Leclercq, T., Hammedi, W. and Poncin, I. (2018), "The boundaries of gamification for engaging customers: effects of losing a contest in online co-creation communities", *Journal of Interactive Marketing*, Vol. 44 No. 1, pp. 82-101, doi: [10.1016/j.intmar.2018.04.004](https://doi.org/10.1016/j.intmar.2018.04.004).
- Lee, M., Cho, M., Gim, J., Jeong, D.H. and Jung, H. (2014), "Prescriptive analytics system for scholar research performance enhancement", *International Conference on Human-Computer Interaction (Ed.), HCI International 2014 – Posters' Extended Abstracts*, Springer, New York, NY, pp. 186-190, doi: [10.1007/978-3-319-07857-1_33](https://doi.org/10.1007/978-3-319-07857-1_33).
- Legner, C., Eymann, T., Hess, T., Matt, C., Böhmman, T., Drews, P., Mädche, A., Urbach, N. and Ahlemann, F. (2017), "Digitalization: opportunity and challenge for the business and information systems engineering community", *Business and Information Systems Engineering*, Vol. 59 No. 4, pp. 301-308, doi: [10.1007/s12599-017-0484-2](https://doi.org/10.1007/s12599-017-0484-2).
- Lenz, R. and Hahn, U. (2015), "A synthesis of empirical internal audit effectiveness literature pointing to new research opportunities", *Managerial Auditing Journal*, Vol. 30 No. 1, pp. 5-33, doi: [10.1108/MAJ-08-2014-1072](https://doi.org/10.1108/MAJ-08-2014-1072).
- Lenz, R. and Hoos, F. (2023), "The future role of the internal audit function: assure. Build. Consult", *EDPACS*, Vol. 67 No. 3, pp. 39-52, doi: [10.1080/07366981.2023.2165361](https://doi.org/10.1080/07366981.2023.2165361).
- Lesage, C. and Ben Saab, E. (2009), "Independence of the auditor", in Colasse, B. (Ed.), *Accounting, Management Control, and Audit Encyclopedia*, 2nd ed., Économica, Paris.
- Lin, S., Pizzini, M., Vargus, M. and Bardhan, I.R. (2011), "The role of the internal audit function in the disclosure of material weaknesses", *The Accounting Review*, Vol. 86 No. 1, pp. 287-323, doi: [10.2308/accr.00000016](https://doi.org/10.2308/accr.00000016).
- Manita, R., Elommal, N., Baudier, P. and Hikkerova, L. (2020), "The digital transformation of external audit and its impact on corporate governance", *Technological Forecasting and Social Change*, Vol. 150, pp. 1-10, doi: [10.1016/j.techfore.2019.119751](https://doi.org/10.1016/j.techfore.2019.119751).
- Mariani, M.M. and Wamba, S.F. (2020), "Exploring how consumer goods companies innovate in the digital age: the role of big data analytics companies", *Journal of Business Research*, Vol. 121, pp. 338-352, doi: [10.1016/j.jbusres.2020.09.012](https://doi.org/10.1016/j.jbusres.2020.09.012).

-
- Mertens, P. and Wiener, M. (2018), "Riding the digitalization wave: toward a sustainable nomenclature in wirtschaftsinformatik", *Business and Information Systems Engineering*, Vol. 60 No. 4, pp. 367-372, doi: [10.1007/s12599-018-0545-1](https://doi.org/10.1007/s12599-018-0545-1).
- Messier, W.F., Jr, Reynolds, J.K., Simon, C.A. and Wood, D.A. (2011), "The effect of using the internal audit function as a management training ground on the external auditor's reliance decision", *The Accounting Review*, Vol. 86 No. 6, pp. 2131-2154, doi: [10.2308/accr-10136](https://doi.org/10.2308/accr-10136).
- Munro, L. and Stewart, J. (2010), "External auditors' reliance on internal audit: the impact of sourcing arrangements and consulting activities", *Accounting and Finance*, Vol. 50 No. 2, pp. 371-387, doi: [10.1111/j.1467-629X.2009.00322.x](https://doi.org/10.1111/j.1467-629X.2009.00322.x).
- Munro, L. and Stewart, J. (2011), "External auditors' reliance on internal auditing: further evidence", *Managerial Auditing Journal*, Vol. 26 No. 6, pp. 464-481, doi: [10.1108/02686901111142530](https://doi.org/10.1108/02686901111142530).
- Mursita, L.Y. and Nahartyo, E. (2022), "How centrality bias in subjective evaluation affects positive and negative employee work behavior: a real-effort task experiment", *Journal of Accounting and Organizational Change*, Vol. 18 No. 5, pp. 789-810, doi: [10.1108/JAOC-01-2020-0002](https://doi.org/10.1108/JAOC-01-2020-0002).
- Nagy, A.L. and Cenker, W.J. (2002), "An assessment of the newly defined internal audit function", *Managerial Auditing Journal*, Vol. 17 No. 3, pp. 130-137, doi: [10.1108/02686900210419912](https://doi.org/10.1108/02686900210419912).
- Naheem, M.A. (2016), "Internal audit function and AML compliance: the globalisation of the internal audit function", *Journal of Money Laundering Control*, Vol. 19 No. 4, pp. 459-469.
- Nunnally, J. (1978), *Psychometric Methods*, McGraw-Hill, New York, NY.
- Oussii, A.A. and Boulila Taktak, N. (2018), "The impact of internal audit function characteristics on internal control quality", *Managerial Auditing Journal*, Vol. 33 No. 5, pp. 450-469, doi: [10.1108/MAJ-06-2017-1579](https://doi.org/10.1108/MAJ-06-2017-1579).
- Palan, S. and Schitter, C. (2018), "Prolific. ac—a subject Pool for online experiments", *Journal of Behavioral and Experimental Finance*, Vol. 17, pp. 22-27, doi: [10.1016/j.jbef.2017.12.004](https://doi.org/10.1016/j.jbef.2017.12.004).
- Peer, E., Brandimarte, L., Samat, S. and Acquisti, A. (2017), "Beyond the Turk: alternative platforms for crowdsourcing behavioral research", *Journal of Experimental Social Psychology*, Vol. 70, pp. 153-163, doi: [10.1016/j.jesp.2017.01.006](https://doi.org/10.1016/j.jesp.2017.01.006).
- Piper, A. (2016), "Attention to detail and focused effort can help internal auditors build the relationships required to be perceived as valued advisers", *Internal Auditor*, The Institute of Internal Auditors, available at: <https://go.gale.com/ps/ido?id=GALE%7CA450695659&v=2.1&it=r&linkaccess=abs&issn=00205745&p=AONE&sw=w&userGroupName=anon%7Eaa69881f> (accessed 22 December 2021).
- Pizzini, M., Lin, S. and Ziegenfuss, D.E. (2015), "The impact of internal audit function quality and contribution on audit delay", *AUDITING: A Journal of Practice and Theory*, Vol. 34 No. 1, pp. 25-58, doi: [10.2308/ajpt-50848](https://doi.org/10.2308/ajpt-50848).
- Prat Dit Hauret, C. (2003), "L'indépendance du commissaire aux comptes: une analyse empirique fondée sur trois composantes psychologiques du comportement", *Comptabilité – Contrôle – Audit*, Vol. 9 No. 2, pp. 31-58, doi: [10.3917/cca.092.0031](https://doi.org/10.3917/cca.092.0031).
- Prawitt, D.F., Sharp, N.Y. and Wood, D.A. (2012), "Internal audit outsourcing and the risk of misleading or fraudulent financial reporting: did Sarbanes-Oxley get it wrong?", *Contemporary Accounting Research*, Vol. 29 No. 4, pp. 1109-1136, doi: [10.1111/j.1911-3846.2012.01141.x](https://doi.org/10.1111/j.1911-3846.2012.01141.x).
- Prawitt, D.F., Smith, J.L. and Wood, D.A. (2009), "Internal audit quality and earnings management", *The Accounting Review*, Vol. 84 No. 4, pp. 1255-1280, doi: [10.2308/accr.2009.84.4.1255](https://doi.org/10.2308/accr.2009.84.4.1255).
- Protiviti (2018), "Analytics in auditing is a game changer", available at: <https://blog.protiviti.com/2018/03/12/analytics-auditing-game-changer-new-protiviti-survey-released/> (accessed 7 August 2020).
- Protiviti (2019a), "Taking on digital: internal auditing around the world", available at: www.protiviti.com/sites/default/files/united_states/insights/ia-around-the-world-v14-protiviti.pdf (accessed 7 August 2020).

- Protiviti (2019b), "Embracing the next generation of internal auditing", available at: www.protiviti.com/sites/default/files/united_states/insights/2019-ia-capabilities-and-needs-survey-protiviti.pdf (accessed 7 August 2020).
- Protiviti and North Carolina State University (2019), "Executive perspectives on top risks 2019: key issues being discussed in the boardroom and C-suite", available at: www.protiviti.com/sites/default/files/united_states/insights/nc-state-protiviti-survey-top-risks-2019.pdf (accessed 7 August 2020).
- PwC (2018), "State of the internal audit profession study. Moving at the speed of innovation: the foundational tools and talents of technology-enabled internal audit", available at: www.pwc.com/sg/en/publications/assets/state-of-the-internal-audit-2018.pdf (accessed 7 September 2020).
- PwC (2019), "Annual global CEO survey: CEOs' curbed confidence spells caution", available at: www.pwc.com/mu/pwc-22nd-annual-global-ceo-survey-mu.pdf (accessed 7 August 2020).
- Rakipi, R., De Santis, F. and D'Onza, G. (2021), "Correlates of the internal audit function's use of data analytics in the big data era: global evidence", *Journal of International Accounting, Auditing and Taxation*, Vol. 42, p. 100357, doi: [10.1016/j.intaccudtax.2020.100357](https://doi.org/10.1016/j.intaccudtax.2020.100357).
- Rickett, L. (2016), "Big data and risk assessment", *Internal Auditing*, Vol. 31 No. 5, pp. 13-17.
- Rittenberg, L.E. and Covalleski, M.A. (2001), "Internalization versus externalization of the internal audit function: an examination of professional and organizational imperatives", *Accounting, Organizations and Society*, Vol. 26 Nos 7/8, pp. 617-641, doi: [10.1016/S0361-3682\(01\)00015-0](https://doi.org/10.1016/S0361-3682(01)00015-0).
- Rose, S., Clark, M., Samouel, P. and Hair, N. (2012), "Online customer experience in e-retailing: an empirical model of antecedents and outcomes", *Journal of Retailing*, Vol. 88 No. 2, pp. 308-322, doi: [10.1016/j.jretai.2012.03.001](https://doi.org/10.1016/j.jretai.2012.03.001).
- Roussy, M. (2013), "Internal auditor's roles: from watchdogs to helpers and protectors of the top manager", *Critical Perspectives on Accounting*, Vol. 24 Nos 7/8, pp. 550-571, doi: [10.1016/j.cpa.2013.08.004](https://doi.org/10.1016/j.cpa.2013.08.004).
- Roussy, M. and Brivot, M. (2016), "Internal audit quality: a polysemous notion?", *Accounting, Auditing and Accountability Journal*, Vol. 29 No. 5, pp. 714-738, doi: [10.1108/AAAJ-10-2014-1843](https://doi.org/10.1108/AAAJ-10-2014-1843).
- Roussy, M. and Perron, A. (2018), "New perspectives in internal audit research: a structured literature review", *Accounting Perspectives*, Vol. 17 No. 3, pp. 345-385, doi: [10.1111/1911-3838.12180](https://doi.org/10.1111/1911-3838.12180).
- Santos, V. and Beuren, I.M. (2022), "How enabling and coercive control systems influence individuals' behaviors? Analysis under the lens of construal level theory", *Journal of Accounting and Organizational Change*, doi: [10.1108/JAOC-02-2022-0026](https://doi.org/10.1108/JAOC-02-2022-0026).
- Schoemaker, P.J.H., Heaton, S. and Teece, D. (2018), "Innovation, dynamic capabilities, and leadership", *California Management Review*, Vol. 61 No. 1, pp. 15-42, doi: [10.1177/0008125618790246](https://doi.org/10.1177/0008125618790246).
- Soh, D.S.B. and Martinov-Bennie, N. (2011), "The internal audit function: perceptions of internal audit roles, effectiveness and evaluation", *Managerial Auditing Journal*, Vol. 26 No. 7, pp. 605-622, doi: [10.1108/02686901111151332](https://doi.org/10.1108/02686901111151332).
- Soh, D.S.B. and Martinov-Bennie, N. (2015), "Internal auditors' perceptions of their role in environmental, social and governance assurance and consulting", *Managerial Auditing Journal*, Vol. 30 No. 1, pp. 80-111, doi: [10.1108/MAJ-08-2014-1075](https://doi.org/10.1108/MAJ-08-2014-1075).
- Stewart, J. and Subramaniam, N. (2010), "Internal audit independence and objectivity: emerging research opportunities", *Managerial Auditing Journal*, Vol. 25 No. 4, pp. 328-360, doi: [10.1108/02686901011034162](https://doi.org/10.1108/02686901011034162).
- Tang, F., Norman, C.S. and Vondrzyk, V.P. (2017), "Exploring perceptions of data analytics in the internal audit function", *Behaviour and Information Technology*, Vol. 36 No. 11, pp. 1125-1136, doi: [10.1080/0144929X.2017.1355014](https://doi.org/10.1080/0144929X.2017.1355014).
- Trapp, I. and Trapp, R. (2019), "The psychological effects of centrality bias: an experimental analysis", *Journal of Business Economics*, Vol. 89 No. 2, pp. 155-189, doi: [10.1007/s11573-018-0908-6](https://doi.org/10.1007/s11573-018-0908-6).
- Troshina, E.P. and Mantulenko, V.V. (2019), "Influence of digitalization on motivation techniques in organizations", *International Scientific Conference Digital Transformation of the Economy: Challenges, Trends, New Opportunities*, pp. 317-323, doi: [10.1007/978-3-030-27015-5_38](https://doi.org/10.1007/978-3-030-27015-5_38).

-
- Trotman, A.J. and Duncan, K.R. (2018), "Internal audit quality: insights from audit committee members, senior management, and internal auditors", *AUDITING: A Journal of Practice and Theory*, Vol. 37 No. 4, pp. 235-259, doi: [10.2308/ajpt-51877](https://doi.org/10.2308/ajpt-51877).
- Tschakert, N., Kokina, J. and Kozlowski, S. (2016), "The next frontier in data analytics", *Journal of Accountancy*, Vol. 222 No. 2, pp. 58-63.
- Verhoef, P.C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J.Q., Fabian, N. and Haenlein, M. (2021), "Digital transformation: a multidisciplinary reflection and research agenda", *Journal of Business Research*, Vol. 122, pp. 889-901, doi: [10.1016/j.jbusres.2019.09.022](https://doi.org/10.1016/j.jbusres.2019.09.022).
- Volodina, T., Grossi, G. and Vakulenko, V. (2022), "The changing roles of internal auditors in the Ukrainian Central government", *Journal of Accounting and Organizational Change*, Vol. 19 No. 6, doi: [10.1108/JAOC-04-2021-0057](https://doi.org/10.1108/JAOC-04-2021-0057).
- Wang, T. and Cuthbertson, R. (2015), "Eight issues on audit data analytics we would like researched", *Journal of Information Systems*, Vol. 29 No. 1, pp. 155-162, doi: [10.2308/isys-50955](https://doi.org/10.2308/isys-50955).
- Yang, L. (2021), "Auditor or adviser? Auditor (in)dependence and its impact on financial management", *Public Administration Review*, Vol. 81 No. 3, pp. 475-487, doi: [10.1111/puar.13313](https://doi.org/10.1111/puar.13313).
- Zwelling, S. (2019), "Redefining internal auditing", *Internal Auditor*, The Institute of Internal Auditors, available at: <https://internalauditor.theiia.org/en/articles/2019/may/redefining-internal-auditing/> (accessed 22 December 2021).
-

Appendix. Experimental case

Assume you are the CEO of Electronic Retail Inc. Based on the information provided below, you will be asked questions related to its internal audit department. Electronic Retail Inc. is based in the USA and listed on the New York Stock Exchange. The company buys and sells to consumers various electronic goods such as smartphones, computers, televisions and household appliances. Electronic Retail Inc. stores are located throughout the USA. Electronic Retail Inc. also sells products to consumers online through its website. In recent years, the company's market share is growing in a stable and continuous way. Electronic Retail Inc. has a culture of continuous improvement of all processes. As part of their objectives, the company wants to become the US market leader through additional penetration therein and by increasing the variety of products available to consumers.

Electronic Retail Inc.'s internal audit department consists of 12 people: one head of internal audit, two managers, three senior internal auditors and six junior internal auditors. These 12 internal auditors are full-time employees and the company does not outsource or co-source any internal audit work:

No Consulting condition: The internal audit department dedicates 100% of its time to assurance activities. This refers to the following activities. First, internal auditors perform compliance audits to evaluate if processes comply with company policies and procedures. Second, they evaluate the efficiency and effectiveness of internal control processes and procedures. Finally, they perform an evaluation of processes and practices against known best practices and when applicable against similar companies. The internal audit department does not perform any consulting activities for management such as improvement or development of processes, involvement in enterprise risk management, or other consulting projects.

Yes Consulting condition: The internal audit department dedicates 50% of its time to assurance activities. This refers to the following activities. First, internal auditors perform compliance audits to evaluate if processes comply with company policies and procedures. Second, they evaluate the efficiency and effectiveness of internal control processes and procedures. Finally, they perform an evaluation of processes and practices against known best practices and when applicable against similar companies. In addition to assurance activities, the internal audit department dedicates 50% of its time to consulting activities for management such as improvement or development of processes, involvement in enterprise risk management, or other consulting projects.

The internal audit department reports to the audit committee of the board of directors. Internal auditors appear to have adequate knowledge of Electronic Retail Inc.'s operations, processes and procedures. Internal audit work appears to be well documented and internal audit staff seems to be adequately supervised.

In line with business objectives, the internal audit department develops the following audit program for each assurance engagement related to processes assessed "high risk":

- The internal auditors conduct interviews with the key personnel involved in the process, including the process owner, to gain process understanding.
- The internal auditors review the trial balance and reconciliations.
- The internal auditors perform transaction testing for appropriate approvals, timeliness of processing and completeness and accuracy of recordings.
- Internal auditors review for compliance with existing policies and procedures, including proper authorization of transactions.
- Internal auditors evaluate IT general and application controls relating to information systems used in the process.
- Audit findings are discussed with process owners during the audit and a draft report is distributed to relevant parties prior to the closing meeting. A formal follow-up process is defined for all open findings from the final report.

No data analytics condition: Internal auditors perform analyses, testing and reviews based on samples. Once a sample is selected, internal auditors perform the following types of analyses:

- They perform for each selected item a manual and detailed check of controls, entries and other relevant documents to detect errors and/or anomalies. This includes identification of missing documents, unexpected variances, improper disbursements and indications of weaknesses in controls.
- They analyze aggregated data to detect unexpected variations.
- They perform ratio and trend analyses for the audit period versus prior periods.

Yes data analytics condition: Internal auditors perform analyses, testing and reviews of full data sets. Once a full data set is extracted, internal auditors perform the following types of analyses:

- They use an application that enables a detailed check of controls, entries and other relevant documents to detect errors and/or anomalies of the entire population. This includes identification of missing documents, unexpected variances, improper disbursements and indications of weaknesses in controls.
- They use an application that enables analysis of aggregated data to detect unexpected variations.
- They use an application that enables prediction of future events by identifying potential trends or clusters and enables users to perform simulations to suggest potential actions or recommendations.

Corresponding author

Nathanaël Betti can be contacted at: nathanael.betti@uclouvain.be

For instructions on how to order reprints of this article, please visit our website:

www.emeraldgroupublishing.com/licensing/reprints.htm

Or contact us for further details: permissions@emeraldinsight.com