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Correlates of the internal audit function's use of data analytics in the Big Data Era: Global evidence

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Abstract

In the big data era, internal audit functions (IAFs) should innovate their techniques so as to add value to their organizations. The use of data analytics (DA) increases IAFs' ability to extract value from big data, helping IAFs to enhance their activities' efficiency and effectiveness. We use responses from 1,681 Chief Audit Executives (CAEs) in 82 countries to investigate the correlates of IAFs' DA usage. From the literature, we identify five main variables expected to be associated with IAFs' DA use. We find a positive and significant association between DA use and (i) the IAF reporting to the audit committee (AC) and (ii) CAEs' ability to build positive relationships with managers. These findings suggest that IAF independence and CAEs' soft skills are important to innovate IAF techniques favoring DA use. We also find a positive association between DA use and IAFs' involvement in the assurance of enterprise risk management, fraud detection, and IT risk audit activities. Our findings contribute to the internal auditing and DA literatures, and should be of interest to CAEs, ACs, corporate boards, and professional associations.

Keywords: internal audit, data analytics, big data, soft skills, fraud detection, IT audit.

1. Introduction

We investigate several variables that are theoretically associated with internal audit functions' (IAFs) uses of data analytics (DA).[1] There is a growing recognition that DA use can improve the efficiency, effectiveness, and timeliness of internal auditing processes in multiple ways. For instance, internal auditors can use DA to better identify risks that are critical to their organization in a timely way, and to help managers enhance risk management processes (Dzuranin & Mălăescu, 2015). DA can also be used to improve audit evidence's appropriateness and sufficiency (Weidenmier & Ramamoorti, 2006). Further, DA may increase the IAF's ability to detect fraud and misconduct (Li, Dai, Gershberg, & Vasarhelyi, 2018; Schneider, Dai, Janvrin, Ajayi, & Raschke, 2015; Tang, Strand Norman, & Vendrzyk, 2017). Despite these potential benefits of DA techniques for internal auditors, studies mainly focus on the use of DA in external auditing (Alles, 2015; Cao, Chychyla, & Stewart, 2015; Vasarhelyi, Kogan, & Tuttle, 2015; Yoon, Hoogduin, & Zhang, 2015), with little attention to the application of DA in internal auditing.

Practitioners report low acceptance and utilization of DA by internal auditors, with noticeable differences among companies (Deloitte, 2016; Grant Thornton, 2017; PriceWaterhouseCoopers, 2014; Protiviti, 2018). We know very little about the factors that influence DA use in internal audit activities. Only one study has tested drivers of DA use (Li et al., 2018), focusing on technological and organizational factors that can impact the post-adoption use of specific DA tools. Li et al. (2018) find that internal auditors' technological competencies, professional standards related to internal auditing, and top management support facilitate DA use. However, the mentioned research is limited in its consideration of corporate-internal contextual attributes (management support and

[1] There are several definitions of DA. One of the most-cited definitions is that DA is the tools set 'that enables discovering and analysing patterns, identifying anomalies, and extracting other useful information in data underlying or related to the subject matter of an audit through analysis, modelling and visualization for the purpose of planning or performing the audit.' (AICPA, 2015, p. 92).

company size) that lead to DA use. Another qualitative study, based on 12 interviews with chief audit executives (CAEs) in the United States (US), indicates that internal auditors' information technology (IT) backgrounds facilitate DA use (Tang et al., 2017).

The literature indicates that the IAF works effectively when the use of IAF techniques is congruent with the processes and activities performed by the IAF, the IAF's relationships with the audit committee (AC) and senior management, and internal auditors' technical and soft skills (Hass, Abdolmohammadi, & Burnaby, 2006; Lenz & Hahn, 2015). We argue that the IAF's reporting lines, the CAE's ability to build positive relationships with managers as well as the IAF's involvement in risk management assurance, fraud detection, and IT audit risks are associated with the IAF's use of DA.

To provide empirical evidence on the factors that influence IAFs' DA use, we use the responses of 1,681 CAEs from different organizations in 82 countries that participated in the 2015 survey by the Institute of Internal Auditors (IIA), known as the Common Body of Knowledge (CBOK) (henceforth referred to as CBOK 2015). We find that moderate or extensive DA use is positively associated with: 1) the IAF's reporting to the AC, 2) the CAE's ability to build positive relationships with managers, and 3) the IAF's involvement in risk management assurance, fraud detection, and IT risk audit activities.

We contribute to the literature in multiple ways. First, we add factors to the research associated with IAFs' uses of technology (Alles, 2015; Bierstaker, Janvrin, & Lowe, 2014; Braun & Davis, 2003; Gonzalez, Sharma, & Galletta, 2012; Li et al., 2018; Vasarhelyi, Alles, Kuenkaikaew, & Littley, 2012) by highlighting that the IAF's relationship with the AC as well as the IAF's activities and soft skills can influence DA use. In contrast to our study, prior research is mainly based on interviews with small groups of CAEs (Tang et al., 2017) and focuses on specific countries and industries (Ahmi, Saidin, & Abdullah, 2015) or clients of audit software vendors (Li et al., 2018), which limits the generalizability of those results.

Second, our findings contribute to the literature on big data's impacts on business processes by analyzing factors that influence the adoption of big data-related technologies in a control function. A growing strand of literature analyzes factors that can foster (or hinder) organizations' use of innovative forms of information processing, such as data analytics, to generate intelligence from high-volume, high-variety, and high-velocity information assets – so-called big data (Court & Barton, 2013; Gandomi & Haider, 2015; Vidgen, Shaw, & Grant, 2017). These studies mainly focus on marketing, sales, production, and supply chain processes, so we know very little about the factors that drive digital transformation in internal auditing processes. Thus, we add to the growing literature on how firms shape internal processes to exploit big data opportunities (Chen, Chiang, & Storey, 2012; Gepp, Linnenluecke, O'Neill, & Smith, 2018).

Third, we add to the literature on IT adoption, which highlights the relevance of individual perceptions and organizational capabilities (Kim, Mannino, & Nieschwietz, 2009; Li et al., 2018; Vasarhelyi et al., 2012). We find that the characteristics of the context in which IT techniques are implemented can influence the extent of their use.

Finally, our work has practical implications. Professional bodies and internal audit practitioners may find it useful to identify the factors that can facilitate the introduction of DA tools into IAFs. This can help CAEs who wish to increase their IAF's DA use. We also enable practitioners to benchmark the extent of DA use in their organizations against our findings.

The remainder of this paper proceeds as follows. In Section 2, we provide an overview of the literature on DA's potential impacts on internal auditing and the hypotheses development. In Sections 3 and 4, we discuss the research design and the results. In Section 5, we summarize the most relevant insights, discuss our study's main implications and limitations, and offer possible paths for future research.

2. Background and Hypotheses Development

2.1. Internal Audit in the Digital Era

Over the past two decades, the vast increase in the volume of data available to organizations and the growing digitalization of business processes have led to the emergence of the so-called "*Now Economy*" (Alles & Gray, 2016; Vasarhelyi, Alles, & Williams, 2010). Digitalization creates both opportunities and threats, and requires organizations to strengthen their abilities to timeously identify, assess, and prevent risks (Krahel, Moffitt, & Vasarhelyi, 2012; Sun, Alles, & Vasarhelyi, 2015). These factors encourage a paradigm shift in auditing practices (Coderre, 2009). As the IAF has a key role in evaluating an entity's internal controls and risk management systems, the advent of the Now Economy makes it clear that the traditional emphasis on backward-looking audit procedures is an outdated philosophy (Cangemi, 2010).

Several authors claim that internal auditors can significantly benefit from the increasing availability of data and tools for data analysis, including DA. Compared to external auditors, internal auditors should be in a better position to exploit DA's opportunities, as they may have privileged access to business and accounting data that can be used to enhance audit processes' efficiency and effectiveness (Dzuranin & Mălăescu, 2015; Li et al., 2018; Schneider et al., 2015; Tang et al., 2017; Vasarhelyi et al., 2015).

DA techniques can help IAFs to improve both their assurance and consulting services. Concerning assurance, corporate governance actors expect the IAF to provide them with a real-time analysis of the control and risk management processes' quality. DA offers the possibility to provide greater assurance. Without sampling limitations, DA allows one to process and analyze vast amounts of data from multiple sources in real time in order to test internal controls, business transactions, and actions implemented to mitigate risks (Alles, Kogan, Vasarhelyi, & Wu, 2008; Vasarhelyi et al., 2010). Corporate governance actors also expect that IAFs help to mitigate fraud risks and that DA can help internal auditors to better meet these expectations. By analyzing a full data population and using structured and unstructured data from various sources, DA can signal potential fraud by increasing IAFs' ability to identify trends, patterns, anomalies, and exceptions in data (Chan, Chiu, & Vasarhelyi, 2018; Tang et al., 2017).

Concerning consultancy services, managers expect IAFs to help them improve business processes' efficiency and effectiveness. Some organizational units are more extensively using big data, such as marketing, supply chain, and customer services (Alles, 2015; Lee, 2016; Vasarhelyi et al., 2015; White & Bond, 2014). So, managers expect that IAFs keep them informed of the current developments in corporate data utilization and are able to make useful recommendations. Via diagnostic, predictive, and prescriptive DA tools, IAFs can exploit the large volume of available data to support senior and middle managers in the identification and analysis of business processes inefficiencies (Coderre, 2015; Kogan, Alles, Vasarhelyi, & Wu, 2010; Li et al., 2018; Schneider et al., 2015). Further, internal auditors can use DA to identify opportunities to streamline business processes as well as to discover and report meaningful trends and patterns to help senior management to focus on the areas with highest risk (Alles, 2015; Lee, 2016; White & Bond, 2014).

2.2. Hypotheses Development

Studies, guidance, and regulations all highlight the importance of a high-quality IAF to have appropriate relationships with the AC and senior managers. From an agency theory perspective, internal audit is an oversight governance mechanism to monitor senior managers' behaviors and to reduce the likelihood of opportunistic behaviors (Adams, 1994; Gramling, Maletta, Schneider, & Church, 2004). In such a perspective, the IAF should help the organization to improve internal controls so as to: 1) prevent financial fraud (Arel, Beaudoin, & Cianci, 2012; Asare, Davidson, & Gramling, 2008; Lin, Pizzini, Vargus, & Bardhan, 2011; Roussy & Perron, 2018); 2) enhance the financial information's reliability (Davidson, Goodwin-Stewart, & Kent, 2005; Prawitt, Smith, & Wood, 2009); and 3) reduce the likelihood of misconduct by managers.

Studies (Brender, Yzeiraj, & Fragniere, 2015; Norman, Rose, & Rose, 2010) underline that when the CAE reports to senior managers, such as the Chief Executive Officer (CEO) or the Chief Financial Officer (CFO), this can impair the IAF's independence and reduce its propensity to detect and report fraud to the AC and the board. This reporting line reduces the objectivity of internal auditors' judgments but can also undermine the adoption of appropriate techniques the IAF can use to more effectively monitor senior management. The presence of a reporting line with senior managers can prevent investment in DA techniques that would increase the IAF's ability to identify whether managers are involved in fraudulent activities or earning management (Amani & Fadlalla, 2017; Bănărescu, 2015; Earley, 2015; Gepp et al., 2018; Moffitt & Vasarhelyi, 2013). In contrast, when the CAE reports to the AC, this can preserve the IAF's independence and can reduce influences on and interferences in the selection of the most suitable tools and techniques for monitoring. These considerations lead to our first hypothesis:

H1. *The presence of a primary reporting line of the IAF to the AC is positively associated with DA use.*

Several commentators note that a necessary precondition of DA use is the possibility to access data useful for auditing purposes (Alles & Gray, 2016; Earley, 2015; Vasarhelyi, 2012; Vasarhelyi & Romero, 2014). The existence of barriers to data access inevitably reduces DA's applicability. Thus, the creation of a single repository of all enterprise data, such as a data lake, is essential to give IAFs the opportunity to do their own analyses. This circumstance indicates that the application of DA is not merely a matter of technical skills, but also requires the ability of persons, such as CAEs and IT managers of the IAF, to break down data silos and build positive relationships with other organizational managers, particularly those in the IT department (Braun, Struthers-Kennedy, & Wishna, 2017). The development of positive relationships with the IT department facilitates communication between internal auditors and data scientists, which enables a co-learning process in order to identify, develop, and implement the DA tools that better satisfy the internal auditors' requirements.

Positive relationships with all managers (not only with those in the IT department) help the IAF to better understand the needs and expectations of top and middle managers regarding both assurance and consulting activities (Trotman & Duncan, 2018). This is important to identify the most suitable DA tools to address their needs and to understand how to use these tools to better satisfy their requirements (D'Onza, Lamboglia, & Verona, 2015).

Finally, the positive relationships between the IAF and the board of directors (including the AC) is crucial to foster the implementation of DA. Practitioners underline that many IAFs fail in implementing DA because they lack the necessary financial support from the board (Coderre, 2015; Verver, 2015). Thus, building positive relationships with the board is very important, as it enables CAEs to have a voice in organizations' IT projects, to impact the setting of priorities for the resource allocation on IT initiatives, to influence data governance, and to steer these projects toward audit purposes (Dzuranin & Mălăescu, 2015).

From the above, we hypothesize:

H2. *CAEs' ability to build positive relationships is positively associated with DA use.*

Corporate governance actors expect the IAF to provide them with an independent assurance of risk management activities' effectiveness. In today's hypercompetitive business environment, risks shift continually, and auditors need to swiftly identify the key events that may threaten an organization's ability to achieve its objectives (Marks, 2013). DA helps auditors to implement a continuous monitoring of the different risk management process steps, which are: 1) risk identification, 2) risk assessment, 3) risk prioritization and response planning, and 4) risk monitoring (Beasley, Clune, & Hermanson, 2005). First, owing to the opportunity to swiftly elaborate more information and to deepen the analysis, DA increases the IAF's ability to monitor the accuracy and completeness of the risks that managers have identified (Coderre, 2009). Second, by redoing risk assessment activities, DA gives internal auditors the possibility to check the reasonability of managers' risk evaluations (Appelbaum & Nehmer, 2017). Third, DA offers the opportunities to test the adequacy of the actions undertaken to mitigate the identified risks, i.e. by comparing the risk treatment results to the expected results. As a substitute for other risk identification and assessment techniques, DA can also be used when organizations do not have a formalized risk management system in place. DA helps the IAF to harness the power of the increased volume and variety of available data to assure the board that the main risks are under control. Lenz and Hahn (2015) and Moeller (2009) indicate that a key characteristic of an effective

IAF is that the employed techniques should be congruent with the activities performed by the IAF. Thus, we posit:

H3. *IAF involvement in risk management assurance is positively associated with DA use*.

One of the most common uses of DA in auditing is fraud detection. It is widely recognized that DA is becoming a *sine qua non* instrument for effective IAF antifraud activities, because with a massive increase in the volume of data that an organization processes, internal auditors are less likely to detect fraud via sampling techniques and other traditional auditing tools (Brown-Liburd & Vasarhelyi, 2015; Gepp et al., 2018; Jans, Alles, & Vasarhelyi, 2014). In the big data era, the adoption of DA tools increase internal auditors' ability to match, group, order, join, or filter a large quantity of structured and transactional data to identify anomalies in the data stream or behavioral patterns that can reveal fraudulent behaviors (Bierstaker et al., 2014; Murphy & Tysiac, 2015).

DA also give internal auditors opportunities to explore unstructured data from numerous and diverse sources, such as contracts and social media, and that can take different formats in order to identify contradictions and anomalies in the data stream. For instance, IAFs can use DA to conduct behavioral analyses on spending trends by examining all cash expenses to determine whether employees are consistently submitting inappropriately high cash expenses (Li et al., 2018). DA can incorporate and process unstructured data from diverse sources into a single analysis framework, improving both the scale and the speed of IAF activities. For instance, IAFs can use DA to analyze security videos to confirm receipt and exit of materials from a company's warehouse in order to prevent, detect, and even deter fraud (Vasarhelyi et al., 2015). All these considerations show that DA use can improve the effectiveness of fraud detection by the IAF and creates a fraud deterrence mechanism (Borthick & Pennington, 2017; Schneider et al., 2015). As noted, the need to align IAF techniques to the activities carried out by the IAF leads us to hypothesize:

H4. *IAF involvement in fraud detection is positively associated with DA use.*

Organizations are increasingly dependent on IT to manage their business (Chaney & Kim, 2007; Hermanson, Hill, & Ivancevich, 2000). Thus, IAFs are required to face the increasing complexity of companies' IT systems and to pay more attention to the risks associated with IT (Nargiz, 2014). A common concern regarding the auditors' possibility to use DA is the quality of the data available for analysis (Li et al., 2018). Studies indicate that data consistency, integrity, and completeness (Dzuranin & Mălăescu, 2015) are necessary preconditions for DA's applicability in control activities. Data quality depends on the effectiveness with which a company's IT system organizes, stores, and manages data.

In a big data environment, the availability of data from multiple sources and formats increases data conflicts. Further, the huge volume and types of data increase concerns regarding integrity (e.g., vs. unauthorized data modification and illegal access) and completeness (e.g., vs. partial records of unfinished transactions). Thus, internal controls are becoming more important to preserve data consistency, integrity, and completeness. The IIA guide (Richards, Oliphant, & Le Grand, 2005) indicates that IT controls should ensure that: 1) data is accurate, complete, authorized, and correct; 2) data is stored and processed properly; and 3) all outputs are accurate and complete. All these considerations indicate that it is necessary for internal auditors to: 1) prepare the field for DA use by devoting considerable efforts to the assessment of IT risks; and 2) evaluate whether the general and application controls over the IT system are able to preserve data quality, such as by performing IT audits (Hall, 2015; Moeller, 2010).

To achieve these objectives in a more complex IT environment, the audit team should have adequate technical skills. However, studies underline that IAFs often lack these skills, that IT audit activities are limited, and that low data quality reduces the possibility to use DA (Cangemi, 2015; Hadden & Hermanson, 2003; Hermanson et al., 2000). The performance of IT audit activities allows IAFs to better understand the risks that underlie a company's IT system and to identify the potentialities to use DA. Further, by performing IT audits, internal auditors develop in-depth knowledge of the organization's IT system so that they can contextualize DA tools to its peculiarities (Li et al., 2018).

From the above, we hypothesize:

H5. *IAF involvement in IT risk-related audit activities is positively associated with the use of DA tools.*

3. Sample Selection and Research Design

3.1. Sample Selection

The Institute of Internal Auditors Research Foundation (IIARF) developed the CBOK 2015 study, which is the largest global survey of the internal audit profession (Islam, Farah, & Stafford, 2018; Eulerich, Henseler, & Köhler, 2017; Bame-Aldred, Brandon, Messier, Rittenberg, & Stefaniak, 2013). We use responses from 1,681 CAEs in 82 countries from the 2015 CBOK survey.

Table 2 presents information about the sample, crossing the distribution of data by region with the organization type (listed vs. unlisted) in Panel A. Panel B crosses the data by Anglo culture countries with the organization type. Panel B shows that the US has the highest percentage of CAE responses (31.7%) and that the largest group of organizations in the sample is unlisted companies (63.5%).

-- Insert Table 2 about here –

3.2. Model Specification

We develop a logistic regression model (the logit model) to analyze the link between the IAF's use of data analytics and our explanatory and control variables. We estimate the following model:

$$\begin{aligned} USEDA = \alpha &+ \beta_1\, AC\_REPORTING + \beta_2\, BUILD\_REL + \beta_3\, RM\_ASSURANCE \\ &+ \beta_4\, FRAUD + \beta_5\, AUDITITRISK + \beta_6\, Financialindustry + \beta_7\, Multinational \\ &+ \beta_8\, Orgsize + \beta_9\, Listed + \beta_{10}\, Iafsize + \beta_{11}\, Daskills + \beta_{12}\, Country + \varepsilon. \end{aligned} \tag{1}$$

where: *USEDA* = 1 if the IAF uses DA tools moderately or extensively, and 0 if the IAF does not use DA tools or uses them minimally. The other variables are defined in Table 1 and are also discussed below.

To create our dependent variable, the use of data analytics (*USEDA*), we use the following question of the CBOK 2015 study: *What is the extent of activity of your internal audit department related to the use of automated tools for data analytics?* The respondents were asked to use a four-point scale (none, minimal, moderate, and extensive). We measure our dependent variable as a binary variable (1 if the IAF uses the tools for DA moderately or extensively, and 0 if the IAF does not use DA tools or uses them minimally).

To construct our first explanatory variable, *AC_REPORTING*, we use the following question: *What is the primary functional reporting line for the CAE or equivalent in your organization?*[2] Thus, our variable = 1 if the primary reporting line for the CAE is the AC, and 0 if the CAE reports

[2] The CBOK question also specifies how *functional* should be interpreted: 'Functional reporting refers to oversight of the responsibilities of the internal audit function, including approval of the internal audit charter, the audit plan, evaluation of the CAE, compensation for the CAE.'

to senior management. The second explanatory variable is *BUILD_REL*, which captures the CAE's ability to build relationships with others. Here, respondents were asked to evaluate the CAE's relationship building proficiency on a five-point scale (from 1 = novice to 5 = expert). The third independent variable is *RM_ASSURANCE*. This dummy variable = 1 if the IAF is required to provide assurance over the whole RM system, and 0 otherwise. Our fourth independent variable, measured as a dummy variable, is *FRAUD* (= 1 if the IAF has the responsibility to detect fraud, and 0 otherwise). Finally, the fifth explanatory variable in our model is *AUDITITRISKS*. This categorical variable is based on the extent to which the IAF audits IT risks (1 = none, 2 = minimal, 3 = moderate, and 4 = extensive).

We include several control variables in our logistic regression model to consider organizational and IAF characteristics that can influence an IAF's DA use. First, regarding organizational characteristics, we consider and control for whether a firm operates in the financial industry (*Financialindustry*). Studies in internal auditing find that the IAF's size, budget, and activities differ between industries (Anderson, Christ, Johnstone, & Rittenberg, 2012; Carcello, Hermanson, & Raghunandan, 2005; Sarens & Abdolmohammadi, 2011) and that IAFs in the financial industry are generally larger, adopt more innovative approaches, and perform a wider range of activities. Second, we include the variables *Multinational* and *Orgsize* as proxies for firm complexity (Abbott, Parker, & Peters, 2010; Carcello et al., 2005), a characteristic that can result in higher risks and can lead to a greater need for the IAF to use DA tools to improve its capacity to assess the quality of risk management and internal controls.

Third, we consider whether a firm is listed (*Listed*), since the internal auditing literature (Sarens, Allegrini, D'Onza, & Melville, 2011) indicates that listed companies use more advanced tools to provide the audit committee and the board with greater assurance concerning risks and internal controls, as required by corporate governance codes for listed companies. We also use variables that capture IAF characteristics, including: *Iafsize*, since increased numbers of internal auditing employees may lead to a greater possibility of internal auditors specializing in the use of DA tools, and *Daskillsrecruit*, which measures whether IAFs consider DA skills to be one of the top five skills by IAFs during the recruiting process. Finally, we control for country (*Country)*.

4. Empirical Results

4.1. Descriptive Statistics

The results show that 54.5% of the IAFs do not use DA tools or use them minimally (*USEDA* = 0), while 45.5% of IAFs use DA tools moderately or extensively (*USEDA* = 1). Table 3 provides a breakdown of independent variables by *USEDA* levels (except the descriptive statistics for the variable *Listed*, which are included in the general information about the sample in Table 2).

-- Insert Table 3 about here --

Regarding the explanatory variables, the results indicate that 80.5% of the IAFs that use DA tools report directly to the AC. The majority of the IAFs that use DA evaluate CAEs' ability to build relationships as advanced and expert (44.3% and 39.2%, respectively). Table 3 also shows that most IAFs that adopt DA tools provide risk management assurance (61.4%). The results indicate that most IAFs that do not use DA tools also do not have the responsibility to detect fraud (73.1%). Further, the majority of the IAFs that use DA tools have moderate or extensive activities relating to IT risk audits (47.6 % and 39.9 % respectively). Regarding our control variables, Table 3 shows that 66.8% of sample firms that use DA tools do not operate in the financial industry and that 38.3% are multinationals. Also, 62.7% of CAEs manage an IAF with fewer than nine employees. Finally, 71.8% of the IAFs that do not use DA tools do not consider DA skills in their recruiting process.

4.2. Regression Analysis

Table 4 presents bivariate Pearson correlation coefficients between the dependent variable *USEDA* and the independent variables, where significant correlations are identified at 0.05 and 0.01 significance levels. As shown in Table 4, there are a few significant correlations, but no correlation coefficients reached the critical level of 0.50 to cause concern for multicollinearity.

-- Insert Table 4 about here --

Table 5 displays our regression results of the dependent variable (*USEDA*) on the explanatory and control variables. We report the coefficients (β) for each variable and their related standard errors, Wald statistics, and significances. We report the overall χ^2 statistic and the model's classification accuracy. The results indicate that the overall χ^2 statistic is highly significant ($p < 0.000$), with an R^2 of 17.2%. The correlation coefficient signs of the explanatory variables are in the expected direction.

-- Insert Table 5 about here --

The results support H1. *AC_REPORTING* is significantly ($p = 0.006$) and positively associated ($\beta = 0.32$) with our dependent variable. Thus, when CAEs report directly to the AC, IAFs are more likely to use DA tools. Our results also support H2. The significant ($p = 0.012$) and positive coefficient ($\beta = 0.15$) of the variable *BUILD_REL* indicates that when CAEs are better able to build relationships with others, this facilitates the use of DA tools. Regarding H3, our results indicate a significant ($p = 0.001$) and positive ($\beta = 0.33$) association between the variable *RM_ASSURANCE* and the use of DA tools. As expected, our results suggest that when the IAFs are involved in RM assurance, they are more likely to use DA. This finding provides support to studies that suggest that IAFs can use DA tools to enhance risk management via continuous monitoring and assessment (Vasarhelyi et al., 2010).

The independent variable *FRAUD* is also significantly ($p = 0.002$) and positively ($\beta = 0.34$) associated with the use of DA tools. This result provides support for H4, which postulates that when IAFs have the responsibility to detect fraud, they are more likely to moderately or extensively use DA tools. This result is consistent with the literature on DA and auditing, according to which the opportunity to overcome sampling limitations as well as test a large amount of structured and unstructured data increases internal auditors' ability to identify fraud (Borthick & Pennington, 2017; Schneider et al., 2015).

Finally, the results indicate that the more the IAFs perform IT risk-related audit activities, the more likely they are to adopt DA tools, providing support for H5. Consistent with Vasarhelyi et al. (2015), this result suggests that performing IT risk-related audit activities makes the IAF more knowledgeable concerning the company's IT system, and that internal auditors can recommend improving the company's IT in a way that facilitates the increased use of DA tools.

Regarding the control variables, we find that *Iafsize* (0.000), *Orgsize* (0.005), and *Daskillsrecruit* (0.000) have significant and positive associations with our dependent variable (*USEDA*). The control variable *Country* is only significant at 0.10 level while the other control variables (*Financialindustry*, *Multinational*, and *Listed*) are not significant.

4.3. Additional Analyses

In our main analysis, the IAF's use of DA tools is measured as a binary variable. The original CBOK question provides a four-point scale for the responses (1 = none, 2 = minimal, 3 = moderate, and 4 = extensive). We estimated a multinomial logistic regression model (not tabulated) by changing the binary dependent variable *USEDA* into a discrete variable with all four values. The results stayed essentially the same compared to the main model's results in Table 5. More specifically, the results of this multinomial logistic regression model indicate that the overall χ^2 statistic (267.46) is highly significant ($p = 0.003$), with a pseudo R^2 of 18.5%, and that all test variables are significant and positively associated with the use of DA tools.

The CBOK 2015 study provides other variables that can be used as alternative measures to our dependent variable. Thus, we estimate our main model by replacing *USEDA* with other dependent variables. First, we construct the dichotomous variable *DA_SUPPORT*, which uses the CBOK question: *How would you describe the use of technology to support internal audit processes in your organization?* The variable = 1 if the CAEs indicate extensive use of technology across the entire audit process, including data mining and analysis, and 0 otherwise. The results of this logistic regression model indicate that the overall χ^2 statistic (64.63) is highly significant ($p < 0.000$), with a pseudo R^2 of 21.5%.

Second, we replace the dependent variable with the variable *DA_VALUE*, which = 1 if mining and analyzing data for management is considered as one of the top five activities that create value for the organization, and 0 otherwise. The results indicate that the overall χ^2 statistic (33.26) is significant ($p = 0.001$), with a pseudo R^2 of 12.6%.

Finally, we use *DA_ACTIVITIES* as a dependent variable to test our model. To construct this variable, we use the CBOK question: *Does your internal audit department use data mining or data analytics for the following activities?* The respondents were asked to choose up to five of the following activities: 1) tests of entire populations rather than sampling; 2) tests for regulatory compliance; 3) identification of possible fraud; 4) potential issues discovered via risk or control monitoring; 5) business improvement opportunities. We construct *DA_ACTIVITIES* as a dummy variable, which = 1 if the IAF uses data mining or data analytics in performing at least one of the activities, and 0 if the IAF does not use data mining or data analytics for any of the five activities. Using *DA_ACTIVITIES* as dependent variable resulted in χ^2 equal to 66.94 ($p < 0.000$), a model classification accuracy of 67.6, and a pseudo R^2 of 21.2%.

To analyze differences between geographic regions, we test the main model, limiting our sample to Anglo culture countries (see Table 2, Panel B). Prior research indicates that internal audit practices are more mature in Anglo countries than in other countries owing to a longer history of the internal auditing profession (Abdolmohammadi & Boss, 2010; Sarens & Abdolmohammadi, 2011). Thus, it is likely that IAFs in these countries are able to innovate the techniques IAFs use in their activities more and that they have more resources to invest in DA. Compared to the results based on the full sample, this subsample resulted in $\chi^2 = 88.8$ ($p < 0.000$), a model classification accuracy of 67.6, and a pseudo R^2 of 22.5. Our explanatory variables are significant and positively associated with the use of DA tools. We also ran additional tests, limiting our sample to other geographical regions, as classified in Table 2's Panel A. Our results using these subsamples still hold in terms of χ^2 (ranging from 30.2 to 67.7), model classification accuracy (from 65.6 to 71.4), and R^2 (from 17.7% to 25%).

Finally, we estimate the main model using only the control variables *Financialindustry*, *Multinational*, *Orgsize*, *Listed*, *Iafsize*, *Daskillsrecruit*, and *Country*. This estimated model presents a lower value of pseudo R^2 (8.5%), compared to our main logistic regression model (pseudo R^2 = 17.2%).

5. Discussion and Conclusions

We identified and tested five variables expected to be associated with the IAFs' use of DA tools. Our findings provide empirical evidence that the IAF reporting to the AC relates positively and significantly to the adoption of DA tools in audit work. Our evidence adds to the literature on the importance of the IAF's independence (Christopher, Sarens, & Leung, 2009; Mutchler, Chang, & Prawitt, 2001). This underlines that the IAF's independence, preserved through direct reporting to the AC, is important so as to avoid the IAF encountering obstacles in the innovation of its techniques, and to have the necessary financial and human resources to support its investments. This is particularly important for DA, as these techniques increase an IAF's ability to identify possible management fraud and internal control deficiencies. A direct functional report to senior managers could slow down, or in the worst scenario, undermine DA use.

Our results show that CAEs' ability to build positive relationships with managers also relates positively and significantly to the IAF's use of DA techniques. These results expand the literature (Li et al., 2018; Tang et al., 2017) by highlighting that the use of DA techniques in IAFs' activities is not merely a matter of internal auditors' technical capabilities, but that soft skills such as relationship building are also important to transform the IAF into a data-driven function. The process of implementing DA techniques requires the IAF to cooperate with managers in the IT department on technical issues, such as the creation of data lakes and the identification of the best DA tools, with managers in other departments, and with corporate governance bodies, including the board and the AC, so as to understand their needs and expectations. This facilitates knowing how to lever DA to increase the value the IAF offers its stakeholders.

Our results also indicate that the involvement of the IAF in risk management assurance and fraud detection are significant correlates to the IAF's use of DA tools. These findings provide further confirmation to studies that indicated that the use of IAF techniques depends on the activity types performed by IAFs (Hass et al., 2006; Lenz & Hahn, 2015). The results also contribute to the research strand on DA and internal auditing by providing empirical evidence of the opportunities DA offer to enhance the IAF's assurance role concerning risk management (Chan et al., 2018; Vasarhelyi et al., 2010). Finally, the positive and significant relationship between the IT risk-related audit activities and the IAF's use of DA is consistent with the literature (Li et al., 2018). This indicates that DA use is facilitated when the IAF does IT audits, as this offers the possibility to improve data quality, and thereby further develop the knowledge of the organization's IT system and data value chains.

Our results help researchers, CAEs, and professional associations to identify factors that can influence DA use. They also suggest additional research into whether DA adoption determines a real increase in IAF effectiveness and in the IAF's ability to satisfy its stakeholders' expectations. Further, we encourage researchers to analyze the application of DA tools by the IAF in other areas, including business process re-engineering and auditing of outsourced processes, to those we considered. We also provide insights to the IIA in order to develop training activities, standards, and practical guidelines for DA use in internal auditing.

Our study has limitations, which open research opportunities. First, as with all survey-based research, responses are influenced by perceptions that may not fully reflect reality. Second, although we use the literature to identify major correlates of IAFs' DA use, and run additional analyses replacing our dependent variable with alternative variables available in the CBOK, there is the possibility of factors missing in the literature and/or in the CBOK study. An investigation of other factors using different research methods, such as qualitative studies, may be an interesting opportunity for future research. Also, an investigation of how DA use is evolving in different regions and how different factors may impact IAFs' DA use in different regions may be an interesting topic for future research.

Third, since the CBOK study did not require survey respondents to indicate the DA tool types they used, we cannot delve into our analysis more to understand whether the correlates vary between the different DA tool types. Future studies may help to overcome this limitation and may test whether the correlates differ between DA tool types.

This study is among the first to empirically test factors that can help IAFs to integrate DA into their audit activities, levering its potential to be more effective in the era of big data.

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Table 1.
Definition of Variables

Variables	Definitions
USEDA	The use of the automated tool for DA by the IAF; value 1 if the IAF uses DA tools moderately or extensively, 0 if the IAF does not use DA tools or uses them minimally.
AC_REPORTING	The primary functional reporting line for the CAE; value 1 if the primary reporting line is the AC, 0 if the CAE reports to management.
BUILD_REL	The CAE's ability to build positive relationships; value from 1 = novice to 5 = expert).
RM_ASSURANCE	Dummy variable equal to 1 if the IAF is required to provide assurance on risk management (RM), and 0 otherwise.
FRAUD	Dummy variable equal to 1 if the IAF has the responsibility to detect fraud, and 0 otherwise.
AUDITITRISKS	Categorical variable indicating the extent to which the IAF audits IT risks; value 1 = none, 2 = minimal, 3 = moderate, 4 = extensive.
Financialindustry	Dummy variable equal to 1 if the primary industry classification of the organization is finance, and 0 otherwise.
Multinational	Dummy variable equal to 1 if the organization operates in more than one independent country, and 0 otherwise.
Orgsize	Natural logarithm of the total assets.
Listed	Dummy variable equal to 1 if the firm is listed, and 0 otherwise.
Iafsize	Number of full-time equivalent employees in the internal auditing department (1 = 1 to 9, 2 = 10 to 49, 3 = 50 to 999, 4 = 1,000 or more).
Daskillsrecruit	Dummy variable equal to 1 if the IAF considers data analytics skills when recruiting staff, and 0 otherwise.
Country	Dummy variables controlling for respondents' countries.

Table 2.

Sample Characteristics (n = 1,681)

Panel A

Region	Listed Company	%	Unlisted Organization	%	Total	%
Africa	35	2.08	95	5.65	130	7.73
Asia and Pacific	202	12.02	155	9.22	357	21.24
Europe	154	9.16	310	18.44	464	27.60
Middle East	25	1.49	57	3.39	82	4.88
North America	152	9.04	258	15.35	410	24.39
South and Central America and the Caribbean	45	2.68	193	11.48	238	14.16
Total	613	36.47	1,068	63.53	1,681	100.00

Panel B

Country	Listed Company	%	Unlisted Organization	%	Total	%
Australia	6	0.36	20	1.19	26	1.55
Canada	19	1.13	35	2.08	54	3.21
New Zealand	3	0.18	6	0.36	9	0.54
South Africa	17	1.01	19	1.13	36	2.14
UK/Ireland	2	0.12	9	0.54	11	0.65
USA	236	14.04	297	17.67	533	31.71
Total Anglo culture countries	283	16.84	386	22.96	669	39.80
Other countries	330	19.63	682	40.57	1,012	60.20
Total	613	36.47	1,068	63.53	1,681	100.00

Table 3.

Descriptive Statistics on Independent and Control Variables by the Dependent Variable USEDA (n = 1,681)

Variables		USEDA			
		Yes (n = 765)	% (45.5)	No (n = 916)	% (54.5)
AC_REPORTING	Yes	616	80.5	647	70.6
	No	149	19.5	269	29.4
BUILD_REL	*1 = Novice*	1	0.1	6	0.7
	2 = Trained	8	1.0	31	3.4
	3 = Competent	117	15.3	211	23.0
	4 = Advanced	339	44.3	387	42.2
	5 = Expert	300	39.2	281	30.7
RM_ASSURANCE	Yes	470	61.4	505	55.1
	No	295	38.6	411	44.9
FRAUD	Yes	235	30.7	246	26.9
	No	530	69.3	670	73.1
AUDITITRISKS	1 = None	16	2.1	85	9.3
	2 = Minimal	80	10.5	232	25.3
	3 = Moderate	364	47.6	390	42.6
	4 = Extensive	305	39.9	209	22.8
Financialindustry	Yes	254	33.2	251	27.4
	No	511	66.8	665	72.6
Multinational	Yes	293	38.3	328	35.8
	No	472	61.7	588	64.2
Orgsize	Mean	0.83		0.68	
	Std. dev.	0.49		0.49	
Iafsize	1 = 1 to 9 employees	480	62.7	747	81.6
	2 = 10 to 49 employees	224	29.3	142	15.5
	3 = 50 to 999 employees	53	6.9	17	1.9
	4 = 1,000 or more employees	8	1.0	10	1.1
Daskillsrecruit	Yes	331	43.3	258	28.2
	No	434	56.7	658	71.8

Notes: Variables defined in Table 1.

Table 4.
Pearson Correlation Matrix

	USEDA	*AC_REPORTING*	*BUILD_REL*	*RM_ASSURANCE*	*FRAUD*	*AUDITITRISKS*	*Financialindustry*	*Multinational*	*Orgsize*	*Listed*	*Iafsize*	*Daskillsrecruit*	*Country*
USEDA	1.000												
AC_REPORTING	0.114**	1.000											
BUILD_REL	0.138**	0.063**	1.000										
RM_ASSURANCE	0.064**	0.037	0.007	1.000									
FRAUD	0.043	-0.044	-0.011	-0.053*	1.000								
AUDITITRISKS	0.270**	0.163**	0.224**	0.017	-0.083**	1.000							
Financialindustry	0.063**	0.167**	0.036	0.126**	-0.125**	0.223**	1.000						
Multinational	0.026	-0.010	0.027	0.025	0.055*	0.091**	-0.114**	1.000					
Orgsize	0.148**	0.096**	0.099**	-0.016	0.029	0.185**	0.132**	0.165**	1.000				
Listed	0.032	0.084**	-0.017	-0.054*	0.043	0.120**	-0.108**	0.337**	0.201**	1.000			
Iafsize	0.195**	0.073**	0.077**	0.018	-0.014	0.208**	0.123**	0.081**	0.274**	0.172**	1.000		
Daskillsrecruit	0.158**	0.071**	0.146**	-0.100**	0.004	0.079**	-0.008	0.029	0.086**	0.050*	0.092**	1.000	
Country	0.021	0.117**	0.064**	-0.090**	-0.015	0.093**	0.047	-0.026	0.104**	0.000	0.009	0.050*	1.000

Notes: * = significance at the 0.05 level; ** = significance at the 0.01 level. Variables defined in Table 1.

Table 5.
Logistic Regression (Dependent variable: *USEDA*)

Variable	Expected sign	B	Sig.	Std. error	Wald
AC_REPORTING	+	**0.32**	**[0.006]*****	**0.127**	**60.410**
BUILD_REL	+	**0.15**	**[0.012]****	**0.068**	**50.051**
RM_ASSURANCE	+	**0.33**	**[0.001]*****	**0.109**	**90.346**
FRAUD	+	**0.34**	**[0.002]*****	**0.118**	**80.156**
AUDITITRISKS	+	**0.59**	**[0.000]*****	**0.071**	**680.904**
Financialindustry		- 0.13	[0.142]	0.123	10.148
Multinational		- 0.09	[0.235]	0.118	0.524
Orgsize		**0.05**	**[0.005]*****	**0.019**	**60.686**
Listed		0.00	[0.250]	0.001	0.456
Iafsize		**0.45**	**[0.000]*****	**0.095**	**220.599**
Daskillsrecruit		**0.57**	**[0.000]*****	**0.112**	**250.945**
Country		**- 0.16**	**[0.092]***	**0.120**	**10.767**
Constant		**- 40.71**	**[0.000]*****	**0.469**	**1,000.854**
Overall chi-square	231.47				
Significance	[0.000]***				
Model's classification accuracy	54.5%				
Nagelkerke pseudo R	17.2%				

Notes: Variables defined in Table 1.
*, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Not required per instructions of Editor Robert K. Larson.