Data Analytics Adoption, Social Support, and Internal Auditor Performance

Evisa Bogdani
Von Allmen School of Accountancy
University of Kentucky
Lexington, KY 40506 USA
evisa.bogdani@uky.edu

Monika Causholli
Von Allmen School of Accountancy
University of Kentucky
Lexington, KY 40506 USA
monika.causholli@uky.edu

Romina Rakipi
Department of Economics and Management
University of Pisa
Pisa PI, 56124 Italy
romina.rakipi@ec.unipi.it

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ABSTRACT

Although data analytics are regarded as indispensable in enhancing auditor performance in the era of rapid technology advancements and big data, the pace of data analytics adoption in internal auditing has been slow. We examine the extent to which social support facilitates internal auditor adoption of data analytics, and whether the use of data analytics is associated with improved internal auditor performance. Using a unique proprietary dataset from a large insurance company in the U.S., we document that peer social support developed through co-participation in company trainings accelerates internal auditor adoption and use of data analytics in internal audit tasks. Further, we find that the extent to which data analytics are used by internal auditors improves auditor performance across different tasks. These findings inform research and practitioners about effective mechanisms that induce auditors' use of data analytics and shed light on the benefits of data analytics for internal audits.

Keywords: data analytics; social support; internal audit performance

I. INTRODUCTION

Data analytics skills are touted as critical for the future of the internal audit profession. However, due to lack of data, we do not know how internal auditors learn to use new analytics tools and whether these tools assist with internal audit tasks, and ultimately, performance. In this study, we examine two related research questions. First, we examine the role of social support in the adoption and use of data analytics tools among internal auditors.[1] Second, we examine whether the extent to which data analytics tools are used in internal audit tasks is associated with internal auditor performance.

Organizations are rapidly embracing technological advancements and are using big data to improve the efficiency and effectiveness of their operations (Gartner 2021).[2] Internal audit functions (IAFs) as the immediate providers of assurance and advisory services should be adequately prepared for opportunities and challenges associated with these advancements in order to keep up with the pace of change and deliver quality assurance to the company (Alles 2015; Christ, Eulerich, and Wood 2019; IIA 2019; Rakipi, De Santis, and D'Onza 2021).[3] The need for data analytics is further accelerated by the Covid-19 global pandemic, which disrupted many business practices and processes, compelling the internal audit profession to innovate even further (Hodge 2021).

Despite the widely accepted presumptions that big data and analytics tools improve outcomes, the pace of data analytics adoption at the organization and individual level does not

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[1] Social support is related to the degree that supervisors and peers encourage and assist with the application of specific skills and competencies on the job (Bates, Holton, Seyler, and Carvalho 2000; Alvelos, Ferreira, and Bates 2015).

[2] Big data is defined as datasets that are too large and complex for businesses' existing systems to handle using their traditional capabilities to capture, store, manage and analyze these data sets. Big Data have four main features called the four Vs—volume, velocity, veracity and variety (Richardson, Chang, and Smith 2021).

[3] Brian Christensen, president of the Internal Audit Foundation at the Institute of Internal Auditors (IIA), recently noted that "The foundation of next-generation internal audit lies in principles such as agility, real-time risk and controls monitoring, dynamic risk assessment, and effective leveraging of data and advanced technologies" (Protiviti 2020).

reflect these contemplations (Wang and Cuthbertson 2015; Eilifsen, Kinserdal, Messier, and McKee 2020; Protiviti 2021). For instance, a survey of chief audit executives (CAEs) and senior internal audit leaders demonstrates slow progress in data analytics adoption, with the majority of respondents reporting that internal audit teams are still in the early stages of implementing data analytics (Protiviti 2021). Prior studies suggest that system complexity (Dowling and Leech 2014; Verma, Bhattacharyya, and Kumar 2018), perceived data reliability (White and Bond 2014), and limited skills for processing diverse data (Vasarhelyi, Alles, Kuenkaikaew, and Littley 2012; Huerta and Jensen 2017; Al-Hiyari, Said, and Hattab 2019) impede the pace at which individuals adopt new technologies. A common approach to overcoming these challenges is for companies to offer standard or customized training (Bedard, Jackson, Ettredge, and Johnstone 2003; Christ et al. 2019). However, transferring knowledge acquired in training is a complex process that may not guarantee the successful application of these tools to the tasks at hand (Baldwin and Ford 1988; Ford, Smith, Weissbein, Gully, and Salas 1998; Bates et al. 2000; Alvelos et al. 2015).

In this study, we take a social network perspective and examine the extent to which social support grounded in the network of peers that co-participate in various training sessions, facilitates the adoption of new data analytics tools in the IAF of a large insurance company in the U.S. Prior evidence on the association between social support and training knowledge transfer is mixed, and depends on the organizational context (Van der Klink, Gielen, and Nauta 2001; Holton, Chen and Naquin 2003; Alvelos et al. 2015). Therefore, the role of social support in enhancing data analytics knowledge and competence in a knowledge-intense profession such as internal auditing remains an important empirical question.

We conjecture that social support grounded in social networks and informal interactions with peers will enable internal auditors to overcome knowledge barriers that arise from complex systems or negative perceptions related to technologies, leading them to recognize the benefits of data analytics tools. Social support from peers can impact the likelihood that internal auditors will adopt new technologies through several mechanisms. First, internal auditors with a large network of connections across several teams within the IAF, will have access to more diverse information and knowledge about how these tools can be used across different tasks (Cummings 2004). Second, connections enable auditors to communicate with their peers information and beliefs about the benefits and drawbacks of data analytics. Prior research shows that communicating with peers can lower auditors' skepticism about these new tools (Austin, Carpenter, Christ, and Nielson 2020). Finally, reaching out to peers for help is less costly to an auditor's reputation, increasing the likelihood of information exchange (Borgatti and Cross 2003).

The use of data analytics can improve internal auditor performance by enabling the auditor to aggregate and analyze an innumerable and diverse volume of data to understand the entity and its related risks.[4] Further, data analytics can enhance continuous auditing and provide real-time assurance (Vasarhelyi, Alles, and Williams 2010) that errors (EY 2017; KPMG 2017), fraud, and noncompliance (Tang, Strand Norman, and Vendrzyk 2017) are identified, and that organizational risks are aligned with internal controls aimed at mitigating those risks (Alles, Kogan, Vasarhelyi, and Wu 2008; Eulerich, Masli, Pickerd, and Wood 2020). Internal auditors can also use data analytics for better visualizations of the data and to deliver more helpful audit reports to stakeholders (Janesko 2021).

Along with the advantages of data analytics, there exist challenges that may offset these positive effects. Internal auditors may over-rely on or may not be able to understand new

[4] In an auditing context, the American Institute of Certified Public Accountants (AICPA) 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 for the purpose of planning or performing the audit" (AICPA, 2017).

technology, leading to oversight of risks and weak performance. Qualitative and analytical research argues that data analytics tools can be beneficial for improving auditor's efficiency and effectiveness; however, there is no empirical evidence on whether using data analytics enhances the performance of internal auditors in practice (Alles 2015; Salijeni, Samsonova-Taddei, and Turley 2019; Walker and Brown-Liburd 2019; Austin et al. 2020; Eilifsen et al. 2020; Eulerich et al. 2020). Therefore, it is essential to analyze empirically whether the use of data analytics is associated with improved performance (Salijeni et al. 2019).

To test our research questions, we obtained proprietary data from the IAF of a large insurance company in the U.S. The data are from firm surveys about internal auditors' data analytics skills and adoption of new data analytics tools during 2019. The data also includes supervisors' performance evaluations, information about the company's training sessions, and auditors' demographic information. To capture the extent to which data analytics tools are used, we rely on surveys that the company prepared and administered before and after the implementation of data analytics and other training sessions. In these surveys, internal auditors respond to questions about their actual use of data analytics in tasks such as continuous auditing, communication, alignment of risks and controls, and alignment of data analytics with business controls objectives.[5] The measure for the extent to which data analytics are used by internal auditors ranges from zero (low use) to five (high use).

To measure social support, we construct a social network of internal auditors using data from training sessions during 2019 (Borgatti and Cross 2003; Everett, Broccatelli, Borgatti, and Koskinen 2018). We consider two auditors to be connected if they attend the same training session.

[5] Aligning data analytics with business control objectives relates to the audit procedure of assigning the appropriate data analytics tool in order to prevent and detect errors/fraud on a timely basis consistent with the control objectives.

An auditor with more connections is considered to enjoy greater social support. The advantage of training data is that they are not self-reported connections, resulting in less bias (Borgatti and Cross 2003; Borgatti and Foster 2003). Research shows that information exchange that occurs among peers during training can lead to incremental knowledge above and beyond the knowledge arising from the training itself (Everett et al. 2018). To proxy for internal auditor performance, we utilize supervisors' evaluations which are on a 1 to 5 scale, ranging from limited awareness (1), general awareness (2), applied knowledge (3), skilled (4), and expert (5). Supervisors provide evaluations on three main areas of competence: internal audit skills, communication skills, and business knowledge skills. We also compute an overall performance measure as the average score of all three categories.

Descriptive statistics show that internal auditors utilize data analytics tools more frequently for the tasks of aligning risks with controls and for communication. In contrast, auditors seem to be more hesitant to employing data analytics in continuous auditing. Our multivariate analyses show that social support is positively associated with data analytics use in the communication and alignment of risks and controls tasks. In economic terms, an additional connection to a peer is associated with 8.5 percentage points increase in the use of data analytics for communication and 11 percentage points increase for alignment of risks and controls. We also find that use of data analytics is positively associated with internal auditor performance. Specifically, using data analytics for alignment of risks and controls and for alignment of data analytics with business control objectives is positively associated with all three individual performance measures; use of data analytics for continuous auditing is positively associated with overall performance; and use of data analytics for communication is positively associated with performance measuring internal audit skills and effective communication. Overall, this evidence suggests that social support is an essential factor in enhancing auditors' data analytics skills and knowledge, consequently increasing the adoption and use of data analytics tools among internal auditors. Further, greater use of data analytics in internal audits improves auditor performance, consistent with the prevailing beliefs.

Our findings contribute to audit research, technology adoption research, and practice. First, we add to the individual technology adoption literature that has studied social relations from an influence perspective (i.e., the perception that supervisors and peers expect me to adopt a new system) and provide mixed evidence. We consider the richness of social connections evolved during training and the potential for exchanging practical knowledge relevant to the specific internal auditing tasks. We complement prior work applying the social perspective in technology adoption by Sykes, Venkatesh, and Gosain (2009) which shows that advice-seeking network size is positively associated with the new system use. Their findings are from a setting where new technology was used in routine tasks such as entering data and processing orders. In contrast, applying complex data analytics in a profession such as internal auditing requires advanced analyses, critical thinking, and professional judgment. When deciding to implement a new system, an auditor needs to ensure that this new approach does not threaten their job quality. We look at the network and support developed among colleagues, and document that large social support has a positive impact on data analytics adoption.

Second, we extend the organizational learning literature on the mechanisms that facilitate training effectiveness (Baldwin and Ford 1988; Holton, Bates, and Ruona 2000; Holton et al. 2003; Bates et al. 2000; Pham, Segers, and Gijselaers 2012). Research that examines the impact of social support on knowledge transfer has produced mixed findings depending on organizational context such as type and culture (Holton et al. 2003; Alvelos et al. 2015). Our results shed some light on these contradictory findings by showing that social support promoted through co-participation in training enhances data analytics knowledge transfer and consequently increases the likelihood of adoption.

Third, our study fills a void in the literature by empirically demonstrating that the adoption of data analytics tools is associated with better internal auditor performance. While prior research shows the expected benefits of data analytics in external auditing (Janvrin, Bierstaker, and Lowe 2008; Wang and Cuthbertson 2015; Eilifsen et al. 2020), our study is the first to empirically document those benefits in internal auditing. Literature has questioned whether auditors can overcome barriers associated with new systems adoption, especially in the early years of implementation or with advanced data analytics (Walker and Brown-Liburd 2019; Austin et al. 2020; Barr-Pulliam, Brazel, McCallen, and Walker 2020; Emett, Kaplan, Mauldin, and Pickerd 2021; Milosavljevic 2021). Finally, the findings of our study have important implications for the internal audit profession. We provide evidence that internal auditors are increasingly adopting advanced data analytics tools, especially when they have strong social support from their peers. This suggests that managers and CAEs should take steps to enhance employee connections through training or informal events.

The remainder of the paper proceeds as follows. Section 2 provides theoretical background and hypotheses development. Section 3 explains the data and research method. Section 4 presents the main results. Finally, section 5 concludes the study.

II. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Social Support and Data Analytics Use

Although organizations have encouraged the implementation of data analytics, the pace of adoption has been slow (Debreceny, Lee, Neo, and Toh 2005; Vasarhelyi et al. 2012; Alles 2015; Wang and Cuthbertson 2015). In the external audit context, Eilifsen et al. (2020) find that despite auditors' positive perception of the usefulness of data analytics tools, the levels of adoption and utilization are low, especially at the more advanced stages, including continuous auditing, predictive analyses, or regressions.

There are a number of challenges associated with the adoption of data analytics. First, the complexity of data analytics tools can deter usage of these new technologies as auditors frequently lack knowledge and expertise to interact with data analytics tools (Walker and Brown-Liburd 2019; Cangemi 2015; Barton and Court 2012), and internal auditors are no exception. A recent survey from the Institute of Internal Auditors indicates that internal auditors score below average on the level of preparedness for technology innovations such as data analytics tools (Christ et al. 2019). Second, while data analytics tools can be used to combine different sources of data, there are challenges with accessing and understanding different types of datasets (Barton and Court 2012). Finally, auditors are skeptical regarding the quality of the underlying data (White and Bond 2014). When deciding to implement a new system, an auditor needs to ensure that this new approach does not threaten their job quality.

Despite these barriers, social support can serve as a mechanism that facilitates adoption of new data analytics tools. Prior research shows that social support can facilitate the learning process related to new technologies and individuals' intention to integrate and use new technologies in the workplace (Facteau, Dobbins, Russell, Ladd, and Kudisch 1995; Tracey, Tannenbaum, and

Kavanagh 1995; Bates et al. 2000; Holton et al. 2003; Venkatesh, Morris, G. Davis, and M. Davis, 2003; Saks, Salas, and Lewis 2014; Huynh, Xanthopoulou, Winefield 2013; Schreurs, Hetty van Emmerik, Günter, and Germeys 2012; Alvelos et al. 2015). Alvelos et al. (2015) show that social support, measured as supervisors' and co-workers' encouragement, has a positive impact on training effectiveness and suggests that employees should expand social ties with others within the organization to improve knowledge transfer. Further, individuals who perceive that the company's environment and senior management are supportive show a stronger intention to use new technology.

In this paper, we take a social network perspective that captures connections between internal auditors to examine how social support from peers impacts adoption and use of data analytics tools. Prior research shows that social connections provide individuals with access to work-related resources, such as information and advice that enhances their knowledge and skills (Borgatti and Foster 2003; Seibert, Kraimer, and Liden 2001; Brass and Krackhardt 1999; Sparrowe, Liden, Wayne, and Kraimer 2001; Hansen 2002; Cross and Cummings, 2004). Sykes et al. (2009) use survey data to show that employees with a higher number of connections, which they perceive would be helpful with a new information system, have a higher propensity to use the new system. Moreover, social networks can speed up innovation adoption (Burt 1987; Johnson 1986) when information about an innovation is not easily available, such as in the first stages of the implementation of data analytics tools, when individuals tend to share information only with those socially close (Johnson 1986). Further, prior research shows that sharing information about costs and benefits of new technologies can lead to a more comprehensive understanding of the data analytics tools, thus reducing auditors' skepticism about the use of these tools despite the possible costs that auditors might encounter (e.g., costs in terms of time and energy to dedicate to learning these tools especially in the first phases of their implementation) (Barton and Court 2012; Austin et al. 2020).

Contrary to prior research that has examined organizational or management support, our study examines how social support received from peers impacts the adoption and use of data analytics tools. This is an important feature of our study because seeking knowledge from peers is less damaging to an individual's reputation and esteem (Borgatti and Cross 2003), therefore leading to greater information exchange and increasing likelihood of adoption. Also, while prior research examines the implementation and use of new information systems in daily routine tasks, we examine the adoption and use of complex data analytics tools in a knowledge-intensive profession that involves critical thinking and professional judgment. Information and knowledge flowing through social networks is especially beneficial when adopting complex systems and tools in a knowledge-intense profession such as internal auditing (Hansen 1999; Cross and Cummings 2004). Therefore, social support can play a crucial role in terms of the quality and relevance of information that individual auditors can access, which would ease the adoption of technologies (Cross and Cummings 2004). Compared to prior studies that use surveys to capture individuals' intention to use a new technology, we use data collected from the actual use of data analytics tools within an organization. Also, contrary to prior studies that rely on individuals' perception about the support they receive from their environment and social connections, we use archival data from internal auditors' participation in different training sessions to capture the amount of social support that auditors receive from their peers (Everett et al. 2018).

Training is commonly utilized to enhance auditors' knowledge and facilitate technology adoption (Bedard et al. 2003; Christ et al. 2019). The organizational learning literature on the mechanisms that facilitate training effectiveness shows that social support is an essential factor in a successful transfer to the workplace of the knowledge acquired from training (Baldwin and Ford 1988; Holton et al. 2000; Bates et al. 2000; Holton et al. 2003; Pham et al. 2012). However, the impact of social support on the application of training knowledge in practice depends on the organizational context, making its effectiveness uncertain (Van der Klink et al. 2001; Holton et al. 2003; Alvelos et al. 2015). Using archival data from training participation is particularly advantageous for investigating the support that auditors receive from their peers for several reasons. Training serves as an important mechanism for employees to form connections and share information with others. Everett et al. (2018) show that participation in the same event facilitates the creation of incremental knowledge that arises from exchanging information with others that goes beyond the learning gained from the training alone.

In-person training allows participants to understand “who knows what”, enhancing auditors’ ability to evaluate the knowledge and skills of others, identify the source of information that is more relevant for their specific tasks, and increases the opportunity to directly connect with experts (Borgatti and Cross 2003). In addition, the value of knowledge sharing is enhanced when individuals have diverse backgrounds (Cummings 2003; Borgatti and Cross 2003; Burt 1992). In our data, participants in training sessions belong to different teams within the IAF, including corporate services (CS), financials (NF), property and casualty (P&C), data analytics (DA), and information technology (IT), suggesting benefits from knowledge sharing. In-person training also allows auditors to have greater opportunities for face-to-face interactions allowing for timelier access to relevant knowledge. For example, during training breaks, auditors have the opportunity to engage in informal conversations with their peers, smoothing the “ask for help” process if future assistance is needed.

Consistent with the idea that social support created during the training sessions is important for knowledge sharing, we expect that internal auditors with more connections formed during training sessions will receive stronger social support that is necessary to successfully implement and use data analytics tools (Walker, Wasserman, and Wellman 1993; Wasserman and Galaskiewicz 1994; Podolny and Baron 1997). Overall, the above arguments lead to our first hypothesis:

H1: There is a positive association between social support and the adoption and use of data analytics tools by internal auditors.

Data Analytics Use and Auditors' Performance

Due to their privileged access to business and accounting data, IAFs are in the best position to leverage data analytics to provide a higher quality audit to their host organizations (Vasarhelyi, Kogan, and Tuttle 2015; Li, Dai, Gershberg, and Vasarhelyi 2018). Prior studies have mainly focused on the use of data analytics for public accounting and external auditors (Davidson, Desai, and Gerard 2013; Alles 2015; Cao, Chychyla, and Stewart 2015; Vasarhelyi et al. 2015; Yoon, Hoogduin, and Zhang 2015) and accounting decisions (Brown-Liburd, Issa, and Lombardi 2015; Cao et al. 2015; Earley 2015; Warren, Moffitt, and Byrnes 2015; Zhang, Yang, and Appelbaum 2015; Kend and Nguyen 2020). A few studies have examined the possible effects of data analytics use for internal auditors using interviews (Austin et al. 2020) or surveys (Eulerich et al. 2020), but to date, there is no empirical evidence using data from the actual use of data analytics tools and its effects on internal auditors' performance.

Internal auditors are the main source of assurance for the board of directors that internal controls are operating effectively, and risks are properly managed (Anderson 2003; Gramling, Maletta, Schneider, and Church 2004). Further, senior management expects internal auditors to deliver consulting services, sharing their insights on possible improvements of business processes and operational efficiency. Data analytics can enhance the efficiency and effectiveness of assurance and consulting services by allowing for timelier audit procedures, examination of a larger amount of data, and visualizations that better illustrate audit evidence and insights.

PricewaterhouseCoopers states that IAFs can implement data analytics for continuous auditing in order to provide real-time analysis of internal controls, risks, and anomalies that could enable quick responses to risk conditions (PWC 2018; Tysiac 2015).[6] Further, data analytics tools enable auditors to test the whole population of detailed transactions and balances (Elder, Akresh, Glover, Higgs, and Liljegren 2013), allowing for the identification of all exceptions and possible misstatements, errors, inefficiencies, frauds, and noncompliance (EY 2017; KPMG 2017; Tang et al. 2017). This approach ensures that risks faced by the organization are matched and aligned to specific internal controls aimed at mitigating those risks (Alles et al. 2008; Vasarhelyi et al. 2010). For example, auditors can use data analytics to analyze security videos to confirm receipt and exit of materials from a company's warehouse in order to understand deficiencies in internal controls (Zhang, Yang, and Appelbaum 2015) and prevent, detect, and deter fraud (Vasarhelyi et al. 2015).

In addition, internal auditors need to implement and utilize the appropriate data analytics tool for specific business control objectives.[7] Different control objectives address different types of risks that specific internal controls should mitigate, and internal auditors with more exposure to different data analytics tools are better able to select the most appropriate one in order to meet the control objective. By aligning different data analytics tools with different business control

[6] Continuous auditing matches auditing practices with new technologies in order to provide stakeholders with more timely assurance (Vasarhelyi et al. 2010).

[7] "A control objective for internal control over financial reporting generally relates to a relevant assertion and states a criterion for evaluating whether the company's control procedures in a specific area provide reasonable assurance that a misstatement or omission in that relevant assertion is prevented or detected by controls on a timely basis" (PCAOB, 2020).

objectives, internal auditors can provide assurance that risks are managed properly, and management is not exposing the organization to a level of residual risk that exceeds the level of risk appetite. For example, for the control objective related to areas highly susceptible to fraud such as cash expenditures, IAFs can analyze spending trends to reveal patterns and identify anomalies (Li et al. 2018). Thus, they can conduct behavioral analyses and examine cash expenses to verify that employees are not constantly submitting high cash expenses.

Finally, data analytics tools can be used to deliver insights from complex and unstructured data (Wixom, Yen, and Relich 2013). Auditors can utilize advanced data analytics tools to obtain more accurate and intuitive visual representations of the data and enhance visualization of audit engagements' results. This will assist in delivering useful reports for different stakeholders, providing insights to improve the effectiveness and efficiency of business processes (Janesko 2021). Different stakeholders have different expectations and needs related to internal auditors' reports. For example, on the consulting side, internal auditors might use data analytics tools to perform sentiment analysis of customers' comments on social media and other platforms, and provide insights in their reports helpful for the marketing department to assist them in keeping the level of costumer satisfaction above the desired level. On the assurance side, internal auditors can use data visualization tools for the reports to the board and audit committees to show if and how managers are keeping the level of risks below the desired level of the company's risk appetite. For example, in recent years boards of directors are increasingly concerned about cybersecurity and data privacy issues. As these issues continue to make headlines, internal auditors could represent a critical assurance source for the board and audit committee that these risks are managed.

Although data analytics tools provide potential benefits to internal audits, information systems research indicates that the value of any new technology stems from the ability of organizations to leverage these technologies rather than the tool itself (Ross, Beath, and Goodhue 1996; Zhu and Kraemer 2005). Janvrin et al. (2008) argue that technology alone does not improve audit effectiveness, but individuals do. Therefore, to the extent that auditors do not clearly understand new technologies, the benefits could be offset by potential negative effects. For example, overreliance on automated audit procedures can result in more manual work if their implementation or use was not done properly (Milosavljevic 2021). Also, although data analytics allows auditors to identify all the exceptions in the entire population of transactions, performing tests to identify anomalies in such a large number of exceptions could be costly (Barr-Pulliam et al. 2020). Moreover, a high number of false positives when using data analytics tools has been shown to lower auditor skepticism toward the red flags identified, with possible negative consequences for audit quality and auditor performance.

Overall, data analytics provide internal auditors with a number of opportunities to improve performance. Considering all the above arguments, we expect that the use of data analytics will have a positive effect on the quality of the work performed by internal auditors and improve their performance. Thus, we state our second hypothesis as follows:

H2: The use of data analytics tools is positively associated with internal auditors' performance.

III. RESEARCH DESIGN

Data

We use proprietary data from the IAF of a public US insurance company. The data are a combination of data analytics surveys about internal auditors' data analytics knowledge, skills, the extent to which data analytics are used, the company's on-site training, and supervisors' performance evaluations for each internal auditor. We complement this data with employees' demographics information. The data analytics surveys were conducted by the company at the beginning and end of 2019. The objective of the surveys was to assess the level of data analytics skills and technology and compare it to a broader skills benchmark, identifying the skills gap. Internal auditors respond to questions about data analytics use and frequency of use in four different areas: continuous auditing, communication, risk and controls, and business controls objectives.

During 2019, the company offered a number of training sessions covering different knowledge areas, including business knowledge, internal audit, information technology, communication skills, and technical skills. In 2019, the company started implementing data analytics at the strategic level and offered intense training to facilitate adoption of data analytics tools. During 2019 the company provided 261 training sessions that focused on both data analytics skills and other skills. Non-data analytics training sessions also included elements related to the implementation of data analytics. Further, internal auditors were presented with practical cases on how to implement and exploit data analytics tools to improve the quality of the job in the different areas covered during the training sessions.[8] While the company requires employee participation in a few of the training sessions, most of the trainings are voluntary. Supervisors' performance evaluations contain skill assessments for each internal auditor. Supervisors evaluate internal auditors' performance based on internal audit, communication, and business knowledge skills. It is important to highlight that the data analytics survey and performance evaluations are conducted from the company for unrelated reasons to our study. This decreases response biases from internal auditors.

[8] Although there might be cases where data analytics were not covered during a training session, we include all the trainings that auditors attended in the construction of our measure, because they provide opportunities for auditors to develop connections with their peers, thus fostering social support.

Data Analytics Use and Social Support

To test our first hypothesis on the association between social support and the use of data analytics tools, we estimate the following model:

$$DAUse = \alpha_0 + \alpha_1\ SocialSupport + \Sigma\alpha_k\ Controls + e \tag{1}$$

In this model, we are interested in the sign and magnitude of the coefficient on *SocialSupport*, $\alpha_{1.}$ We expect α_1 to be positive and significant, indicating that an auditor with stronger social support (i.e., more connections to other auditors with knowledge) is more likely to use data analytics in performing their own tasks.

Data Analytics Use

In model (1), *DAUse* represents the level of data analytics use by internal auditors and is proxied by a vector of four different dependent variables. In the context of this company, data analytics use refers to visualization tools (Tableau, Power BI, Shiny, Plotly), data preparation tools (Paxata, Alteryx), and advanced analytics (R, Python, Java, Julia, Go), MS Excel, statistics, AI, RPA, and continuous auditing. The dependent variable measures the auditor's rating on how frequently they use data analytics in continuous auditing (*DAUse_Continuous_Auditing*), communication (*DAUse_Communication*), aligning data analytics with risks and controls (*DAUse_Risks_&_Controls*), and aligning data analytics with business control objectives (*DAUse_Bus_Control_Objectives*).

Figure 1 shows frequency distributions of data analytics use for each area *DAUse_Continuous_Auditing*, *DAUse_Communication*, *DAUse_Risks_&_Controls*, and *DAUse_Bus_Control_Objectives*. *DAUse_Continuous_Auditing.* Whereas, for the actual use of data analytics in other areas, the majority of internal auditors' ratings range between four and five. This figure suggests that data analytics is mostly used for aligning risks and controls, as it would be expected for the internal audit profession.

Social Support

We use training data to construct the social network of internal auditors that emerges from co-participation in training sessions. We begin our sample with 86 internal auditors that participated in the 2019 training sessions. Even though we drop some of the participants due to missing data on performance evaluations (31), and data analytics scores (10), we include them in the construction of the network because they are potential sources of knowledge for our sample of internal auditors. Our final sample for the multivariate analyses is composed of 45 internal auditors. Specifically, two auditors are connected if they participate in the same training on a given day. *SocialSupport* is equal to the number of people that co-participated in the same training session at least one time with the auditor. We conjecture that these training sessions assist internal auditors in learning "who knows what" and create opportunities to reach out to other participants during breaks or after the training. Informal breaks allow for socializing and connecting with "experts," making it easier to reach out for assistance in the future. These are crucial for harvesting the benefits of knowledge-sharing in an organization (Borgatti and Cross 2003).

Control Variables

In Equation 1, *Controls* is a vector of control variables that measure internal auditors' characteristics that may influence the extent to which they use data analytics and the size of their social network. Specifically, we control for hours of training on data analytics (*LnDA_Training*) because training sessions are likely to increase data analytics competence and knowledge, leading to increased *DAUse* (Bedard et al. 2003; Vasarhelyi et al. 2015). We also control for previous data analytics competence and knowledge measured by *Past_DAScore*, and *CISA*. *Past_DAScore* is the perceived internal auditor's competence and data analytics prior to the training, ranging from one to ten. *CISA* is an indicator variable set to one when an auditor is a Certified Information Systems Auditor, zero otherwise. *Gender* equals one for males and zero for females. Finally, we include tenure (*LnTenure)*, measured as the number of years an auditor has worked in the company, to control for previous business knowledge and competence (Venkatesh et al. 2003; Mahzan and Lymer 2014).

Data Analytics Use and Internal Auditor Performance

We use the following model to test our second hypothesis testing the association between the extent of data analytics use and internal auditor performance:

$$IA\_Performance = \beta_0 + \beta_1\, DAUse + \Sigma\beta_k\, Controls + e \tag{2}$$

Internal Auditor Performance

To determine *IA_Performance,* we use supervisors' evaluations for internal auditors ranging from one to five, indicating *Limited Awareness, General Awareness, Applied Knowledge, Skilled and Expert,* respectively.[9] Supervisors' evaluations consist of a set of skills that are classified into three main categories: internal audit skills, communication skills, and business knowledge skills. Using these ratings, we create four performance measures as our dependent variables:

- *Overall_Performance*: The average score for all knowledge areas.
- *Internal_Audit_Performance*: The average score of internal audit skills.
- *Communication_Performance*: The average score of soft skills.

[9] Appendix A provides a detailed explanation for each level of performance rating.

- *Business_Knowledge_Performance*: The average score of business knowledge skills.

In Equation 2, the primary independent variable is *DAUse* which is proxied by *DAUse_Continuous_Auditing*, *DAUse_Communication*, *DAUse_Risks_&_Controls*, and *DAUse_Bus_Control_Objectives*, as previously defined.

We control for factors that may be associated with an internal auditor's performance as well as *DAUse*. Specifically, we include a measure that captures prior perception of data analytics competence (*Past_DAScore*) and *SocialSupport* (Bedard et al. 2003; Borgatti and Cross 2003; Cross and Cummings 2004). We also control for total hours of training in all knowledge areas (*LnALL_Training)* since the performance measure captures broader skill and competence areas that may be learned from all training. Finally, we control for *CPA_CIA*, an indicator variable equal to one when the internal auditor is a CPA or CIA (Tang et al. 2017).

IV. RESULTS

Descriptive Statistics

Table 1 shows the descriptive statistics for all variables. Panel A shows the descriptive statistics for our measures of *DAUse*. *DAUse_Continuous_Auditing* has the lowest mean score (2.93), followed by *DAUse_Bus_Control_Objectives* (2.96). In comparison, *DAUse_ Communication* and *DAUse_Risks_&_Controls* have a higher mean score (median) equal to 3.11 (3), suggesting that internal auditors use data analytics more extensively for aligning risks and controls as well as to communicate results.

Panel B presents the statistics for internal auditor performance variables. The *Overall_Performance* mean (median) is 3.22 (3.34). On average, auditors have the highest performance in communication (mean 3.76), while the lowest performance is in business knowledge (mean 3.02). Panel C shows descriptive statistics for other variables. The average *SocialSupport* is about 79 ties, with a minimum (maximum) of 60 (85) denoting extensive social support. On average, auditors have attended 110 *DA_Training* hours, ranging from 2.5 to 568 hours. About 67 percent of the sample are males, and the average tenure is about five years. Regarding certifications, 18 percent of auditors have a CISA, and 31 percent have a CPA or CIA certificate. Finally, the mean (median) *Past_DAScore* is 4.41 (4.09), ranging from 2.2 to 8.13, suggesting a considerable variation on auditors' previous data analytics knowledge.

Table 2 presents the Pearson Correlations of our main and control variables. It appears that all *DAUse* variables are significantly correlated with all four internal auditor performance outcomes, with coefficients varying between 0.28 and 0.45. *SocialSupport* is significantly correlated with performance measures. Also, *LnDA_Training* and *LnALL_Training* are significantly correlated with performance measures. As expected, *Past_DAScore* is correlated with *DAUse* measures.

Tests of Hypothesis 1: Data Analytics Use and Social Support

The OLS results for H1 are presented in Table 3 for *DAUse_Continuous_Auditing*, *DAUse_Communication*, *DAUse_Risks_&_Controls*, and *DAUse_Bus_Control_Objectives*, in columns one to four, respectively. The measures for the goodness of fit range from 20 to 35 percent. In H1, we propose that social support proxied by the number of training ties is positively associated with the use of data analytics. We find a positive and marginally significant coefficient for *SocialSupport* when the dependent variable measures the extent of data analytics use in communication (*DAUse_Communication*, $\alpha = 0.085$, $p = 0.097$) and a positive and significant coefficient when it measures use of data analytics in risk and controls (*DAUse_Risks_&_Controls*,

α = 0.110, p = 0.035). In terms of economic significance, an increase of one connection in *SocialSupport* is associated with an 8.5 percentage points increase in *DAUse_Communication* and 11 percentage points increase in *DAUse_Risks_&_Controls*. Although the coefficients for *DAUse_Continuous_Auditing* and *DAUse_Bus_Control_Objectives* are positive, they are not statistically significant. From our discussion with the company's vice president and CAE, this result can be explained by the slow pace at which data analytics are used for continuous auditing. Further, alignment of data analytics with business controls objectives might require more time to be achieved**,** and as indicated from descriptive statistics, this is where these tools were used the least.

In terms of control variables, it appears that *Past_DAScore* is positive and significantly associated with *DAUse*, across all measures suggesting that prior experience with data analytics helps with the extent to which data analytics tools are used. *CISA* is positively related to *DAUse_Continuous_Auditing* and *DAUse_Communication.* Surprisingly, *DA_Training* is not significantly related to *DAUse* variables. This result somehow implies that longer training is not sufficient to compel auditors to use data analytics tools.

Tests of Hypothesis 2: Data Analytics Use and Internal Auditor Performance

Table 4 shows the results of H2, in which we propose a positive association between *DAUse* and internal auditor performance. Panel A, columns one to four, presents the results for *DAUse_Continuous_Auditing* and four performance measures, *Overall_Performance, Internal_Audit_Performance, Communication_Performance,* and *Business_Knowledge_Performance*. The coefficient of *DAUse_Continuous_Auditing* is positive and significant across all internal audit performance measures. This suggests an improvement in internal auditor's performance with the increase in the use of data analytics for continuous auditing, especially on internal auditing tasks/skills.[10] Regarding control variables, *SocialSupport* is positively related to *Internal_ Audit_Performance* and *Communication_Performance* but is not associated with *Business_ Knowledge_Performance*.

Panel B presents the results the association between *DAUse_Communication* and all performance measures. It appears that *DAUse_Communication* is positive and significantly related with *Overall_Performance* (α = 0.126, p = 0.027), *Internal_Audit_Performance* (α = 0.122, p=0.050), and *Communication_Performance* (α = 0.181, p = 0.008), but not statistically significant for *Business_Knowledge_Performance* (α = 0.099, p = 0.121). Among control variables, *LnALL_Training* is positively related to *Communication_Performance*, consistent with findings in prior literature (Bedard et al. 2003). *SocialSupport* is positively related to *Internal_ Audit_Performance*, and *LnTenure*, as expected, is positively associated with *Business_ Knowledge_Performance*, since the longer one works with the company the more likely they are to gain business knowledge.

Panel C shows the results for the association between *DAUse_Risks_&_Controls* and internal auditor performance measures. We find positive and significant coefficients on *DAUse_Risks_&_Controls*, for *Overall_Performance* (α = 0.170, p = 0.003), *Internal_Audit_ Performance* (α = 0.164, p = 0.008), *Communication_Performance* (α = 0.201, p = 0.004), and *Business_Knowledge_Performance* (α = 0.150, p = 0.019). These results suggest substantial benefits from data analytics adoption on risks and controls by internal auditors, as is often argued by IIA (IIA 2019). In terms of controls, *LnALL_Training* hours is positively related to

[10] This is common sense because data analytics skills/competence are listed as part of internal audit performance in the supervisor's evaluation.

Communication_Performance, and *LnTenure* is positively associated with *Business_Knowledge_Performance.*

The results for the association between *DAUse_Bus_Control_Objectives* and internal auditor performance measures are presented in Panel D. The coefficients on *DAUse_Bus_Control_Objectives* are positive and statistically significant across all performance measures. Regarding control variables, it appears that *LnALL_Training* hours is positively related to *Communication_Performance, SocialSupport* is positively related with *Internal_Audit_Performance* and *Communication_Performance*, and *LnTenure* is positively associated with *Business_Knowledge_Performance*. Overall, these results suggest that use of data analytics in different internal audit tasks has a positive association with internal auditor performance. These results are consistent across all *DAUse* and performance measures. The association is weaker for *DAUse_Continuous_Auditing* and *Communication_Performance* and *Business_Knowledge_Performance.*

V. CONCLUSION

The purpose of this paper is to understand the role of social support in the adoption and use of data analytics tools among internal auditors and examine whether the extent to which data analytics are used can impact internal auditor performance. Using proprietary data from the IAF of a large public insurance company in the U.S., enables us to provide empirical evidence on the factors and role of data analytics in internal audit.

Our results provide evidence that social support is a crucial factor in the process of learning about and utilizing data analytics tools. Social support that emerged from co-participation during trainings enhances data analytics knowledge transfer and ultimately increases internal auditors' use of data analytics, especially for the tasks related to communicating the results and aligning risks and controls. In addition, our results provide evidence that the use of data analytics is associated with higher internal auditor performance, supporting our second hypothesis. Specifically, using data analytics tools for continuous auditing is positively associated with internal auditor overall performance. Further, using data analytics tools for communication is positively associated with internal audit skills and effective communication. Finally, using data analytics to align risks and controls, and alignment of data analytics with business control objectives is positively associated with internal audit performance in all areas.

Our findings contribute to internal audit research, technology adoption research, and practice in several ways. First, we extend the technology adoption literature examining the role of social support in the adoption and use of complex data analytics tools in a knowledge-intensive profession such as internal audit. Eilifisen et al. (2020) contend that more research is needed to better understand how to assist auditors in increasing data analytics use and gaining the best output from the application of advanced data analytics tools. Second, we add to the organizational learning literature on the mechanisms enabling the transfer of knowledge acquired during trainings. We show that co-participation in training promotes social support that enables internal auditors to transfer knowledge on data analytics tools, increasing their adoption and use. Third, our study is the first to provide empirical evidence of the benefits of data analytics for the internal audit profession. Finally, our findings should be of interest to practitioners as we provide evidence that the adoption and use of advanced data analytics tools by internal auditors is facilitated by inducing stronger social support among peers.

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APPENDIX A

Supervisor Performance Rating Guidelines

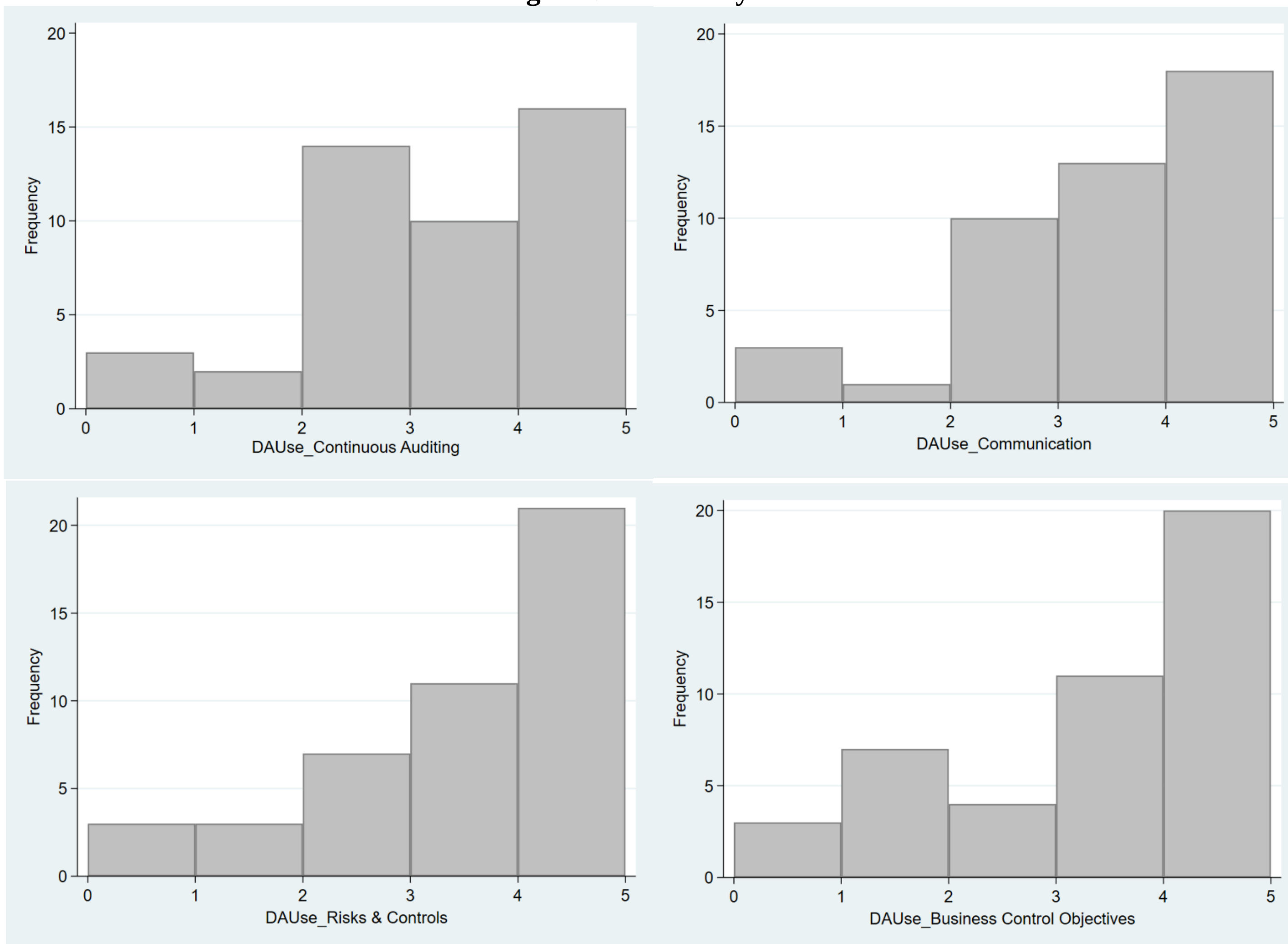
Proficiency Level	Description
1-Limited Awareness	• Is aware of the task/skills/knowledge • Follows instructions under the direct supervision
2-General Awareness	• Can perform routine tasks under normal business conditions • Can perform some of the applied tasks • Can perform most of the applied tasks with limited supervision
3-Applied Knowledge	• Apply task/skills/knowledge accurately and independently
4-Skilled	• Demonstrate advanced task/skills/knowledge • Use insight from his knowledge to coach or supervise others • Can perform complex tasks independently
5-Expert	• Apply foresight to help senior management and the board guide the organization • Assist management to identify innovative approaches to mitigate risks • Provide subject matter expertise to others in addressing situations with higher complexity • Serve as a role model

APPENDIX B
Variable Description

Variable	**Description**
DAUse_Continuous_Auditing	Internal auditor score (0-5) of data analytics use frequency for continuous auditing. *Question: How Often Do You...Identify use cases for continuous auditing?*
DAUse_Communication	Internal auditor score (0-5) of data analytics use frequency for communicating results of analyses. *Question: How Often Do You...Communicate results of data analysis?*
DAUse_Risks_&_Controls	Internal auditor score (0-5) of data analytics use frequency for aligning risks and controls. *Question: How Often Do You...Align risks and controls with data analytics?*
DAUse_Bus_Control_Objectives	Internal auditor score (0-5) of data analytics use frequency for aligning business control objective with data analytics. *Question: How Often Do You...Align data analytics with business control objectives?*
Overall_Performance	Supervisor overall evaluation 2019. The rating varies: 1-Limited Awareness; 2-General Awareness; 3-Applied Knowledge; 4-Skilled; 5-Expert.
Internal_Audit_Performance	Supervisor evaluation on internal audit skills (average scores of ratings on different internal audit skills). The rating varies: 1-Limited Awareness; 2-General Awareness; 3-Applied Knowledge; 4-Skilled; 5-Expert.
Communication_Performance	Supervisor evaluation on soft skills (average scores of ratings on different soft skills). The rating varies: 1-Limited Awareness; 2-General Awareness; 3-Applied Knowledge; 4-Skilled; 5-Expert.
Business_Knowledge_Performance	Supervisor evaluation on business acumen skills (average scores of ratings on different business acumen skills). The rating varies: 1-Limited Awareness; 2-General Awareness; 3-Applied Knowledge; 4-Skilled; 5-Expert.
DA_Training	Internal auditor training hours in data analytics.
LnDA_Training	Natural log of one plus training hours in data analytics.

ALL_Training	Internal auditor training hours in all knowledge areas.
LnALL_Training	Natural log of one plus training hours in all knowledge areas.
SocialSupport	Internal auditor degree centrality in the network constructed using co-participation in 2019 trainings.
Gender	Indicator variable set to one when the internal auditor is male, zero otherwise.
Tenure	Internal auditor tenure (years) with the company.
LnTenure	Natural log of one plus tenure (years) with the company.
CISA	Indicator variable set to one when an internal auditor is a Certified Information Systems Auditor (CISA), zero otherwise.
CPA_CIA	Indicator variable set to one when an internal auditor has a CPA or CIA certificate; zero otherwise.
Past_DAScore	Internal auditor perceived data analytics proficiency score from data analytics survey at the beginning of 2019.

FIGURE 1
Histogram: Data Analytics Use



This table presents the frequency distribution for the actual use of data analytics by internal auditors in four main areas: continuous auditing, communication, risks and controls, and aligning data analytics with business control objectives. The range of data analytics use varies from a minimum of zero to a maximum of five.

TABLE 1
Descriptive Statistics

Panel A: Data Analytics Variables

Variable	N	Mean	SD	Min	P25	P50	P90	Max
DAUse_Continuous_Auditing	45	2.93	1.42	0.00	2.00	3.00	5.00	5.00
DAUse_Communication	45	3.11	1.37	0.00	2.00	3.00	5.00	5.00
DAUse_Risks_&_Controls	45	3.11	1.39	0.00	2.00	3.00	5.00	5.00
DAUse_Bus_Control_Objectives	45	2.96	1.46	0.00	2.00	3.00	5.00	5.00

Panel B: Performance Variables

Variable	N	Mean	SD	Min	P25	P50	P90	Max
Overall_Performance	45	3.22	0.59	1.45	3.03	3.34	3.79	4.15
Internal_Audit_Performance	45	3.27	0.58	1.64	3.07	3.43	3.79	4.07
Communication_Performance	45	3.76	0.73	2.00	3.33	4.00	4.67	5.00
Business_Knowledge_Performance	45	3.02	0.70	1.08	2.78	3.00	3.83	4.25

Panel C: Other Variables

Variable	N	Mean	SD	Min	P25	P50	P90	Max
SocialSupport	45	78.91	4.94	60.00	79.00	80.00	83.00	85.00
DA_Training	45	109.68	135.93	2.50	32.00	55.00	341.50	567.50
ALL_Training	45	253.47	280.62	45.50	107.00	115.70	766.92	1,030.75
Gender	45	0.67	0.48	0.00	0.00	1.00	1.00	1.00
Tenure	45	5.34	6.15	0.27	1.96	3.68	8.77	34.56
CISA	45	0.18	0.39	0.00	0.00	0.00	1.00	1.00
CPA_CIA	45	0.31	0.47	0.00	0.00	0.00	1.00	1.00
Past_DAScore	45	4.41	1.56	2.22	3.21	4.09	7.16	8.13

This table presents descriptive statistics for all our main and control variables. Panel A shows the statistics for our data analytics variables from the internal auditor data analytics surveys. Panel B shows the statistics for performance measures from supervisors' evaluations in three main skill categories. Panel C presents the statistics for all other variables that are from training and demographics datasets. All variables are defined in Appendix B.

TABLE 2
Pearson Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
DAUse_Continuous_Auditing (1)	1.00															
DAUse_Communication (2)	0.86	1.00														
	0.00															
DAUse_Risks_&_Controls (3)	0.85	0.90	1.00													
	0.00	0.00														
DAUse_Bus_Control_Objectives (4)	0.86	0.82	0.90	1.00												
	0.00	0.00	0.00													
Overall_Performance (5)	0.37	0.39	0.44	0.41	1.00											
	0.01	0.01	0.00	0.01												
Internal_Audit_Performance (6)	0.35	0.38	0.45	0.38	0.92	1.00										
	0.02	0.01	0.00	0.01	0.00											
Communication_Performance (7)	0.32	0.42	0.45	0.40	0.69	0.55	1.00									
	0.03	0.00	0.00	0.01	0.00	0.00										
Business_Knowledge_Performance (8)	0.30	0.28	0.32	0.33	0.94	0.76	0.60	1.00								
	0.05	0.06	0.03	0.03	0.00	0.00	0.00									
LnDA_Training (9)	0.19	0.14	0.11	0.21	0.38	0.25	0.42	0.39	1.00							
	0.22	0.38	0.45	0.17	0.01	0.09	0.00	0.01								
SocialSupport (10)	0.14	0.18	0.20	0.17	0.49	0.38	0.53	0.49	0.53	1.00						
	0.38	0.25	0.18	0.26	0.00	0.01	0.00	0.00	0.00							
Gender (11)	0.07	0.09	0.09	0.04	0.23	0.20	0.11	0.24	0.15	0.02	1.00					
	0.66	0.54	0.55	0.78	0.13	0.19	0.47	0.12	0.33	0.92						
LnTenure (12)	0.03	0.04	-0.01	0.07	0.41	0.17	0.39	0.56	0.29	0.50	0.15	1.00				
	0.83	0.77	0.96	0.65	0.00	0.26	0.01	0.00	0.06	0.00	0.32					
LnALL_Training (13)	0.15	0.09	0.09	0.11	0.34	0.18	0.50	0.39	0.81	0.52	0.14	0.32	1.00			
	0.31	0.56	0.56	0.47	0.02	0.24	0.00	0.01	0.00	0.00	0.35	0.03				
CISA (14)	0.27	0.22	0.22	0.22	0.31	0.29	0.21	0.28	0.30	0.14	0.33	0.14	0.20	1.00		
	0.07	0.15	0.15	0.16	0.04	0.06	0.16	0.06	0.05	0.36	0.03	0.35	0.20			
CPA_CIA (15)	0.17	0.09	0.19	0.12	0.15	0.03	0.32	0.20	0.22	0.30	0.27	0.45	0.39	0.19	1.00	
	0.27	0.57	0.21	0.43	0.32	0.84	0.03	0.18	0.14	0.05	0.07	0.00	0.01	0.21		
Past_DAScore (16)	0.57	0.48	0.42	0.49	0.27	0.25	0.11	0.26	0.29	0.02	0.23	0.06	0.26	0.06	0.05	1.00
	0.00	0.00	0.00	0.00	0.08	0.10	0.49	0.09	0.05	0.92	0.12	0.67	0.08	0.70	0.74	

This table shows the pairwise Pearson Correlation coefficients and p-values.

TABLE 3
Data Analytics Use and Social Support

	(1) *DAUse_Continuous_Auditing* *Coeff* *(t-stat)*	(2) *DAUse_Communication* *Coeff* *(t-stat)*	(3) *DAUse_Risks_&_Controls* *Coeff* *(t-stat)*	(4) *DAUse_Bus_Controls_Objectives* *Coeff* *(t-stat)*
SocialSupport	0.061	0.084*	0.110**	0.062
	(1.30)	(1.70)	(2.18)	(1.18)
LnDA_Training	-0.178	-0.245	-0.284	-0.109
	(-0.96)	(-1.26)	(-1.43)	(-0.52)
CISA	1.144**	0.882*	0.897	0.891
	(2.31)	(1.70)	(1.68)	(1.59)
Past_DAScore	0.577***	0.480***	0.439***	0.496***
	(4.79)	(3.80)	(3.39)	(3.64)
Gender	-0.449	-0.212	-0.134	-0.428
	(-1.12)	(-0.51)	(-0.31)	(-0.95)
LnTenure	-0.180	-0.197	-0.369	-0.115
	(-0.65)	(-0.68)	(-1.24)	(-0.37)
Constant	-3.313	-4.329	-5.850	-3.403
	(-0.99)	(-1.24)	(-1.63)	(-0.90)
N	45	45	45	45
R2	0.43	0.33	0.31	0.32
Adj_R2	0.35	0.23	0.20	0.21

This table presents the results for the association between social support and the use of data analytics. The main independent variable is social support (*SocialSupport)*. The dependent variables are the individual internal auditor level of data analytics use for different purposes: continuous auditing *(DAUse_Continuous_Auditing)*, communication *(DAUse_Communication)*, risk and controls *(DAUse_Risks_&_Controls)* and align data analytics with business control objectives *(DAUse_Bus_Control_Objectives).* Columns 1 through 4 present the results for the association of *SocialSupport* with all dependent variables, *DAUse_Continuous_Auditing*, *DAUse_Communication*, *DAUse_Risks_&_Controls*, *and DAUse_Bus_Control_Objectives*, respectively. All variables are winsorized at 1% and 99%. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

TABLE 4
Data Analytics Use and Internal Auditor Performance

Panel A: Data Analytics Use for Continuous Auditing

	(1) ***Overall_ Performance*** ***Coeff (t-stat)***	**(2)** ***Internal_Audit_ Performance*** ***Coeff (t-stat)***	**(3)** ***Communication_ Performance*** ***Coeff (t-stat)***	**(4)** ***Business_Knowledge_ Performance*** ***Coeff (t-stat)***
DAUse_Continuous_Auditing	0.124**	0.119**	0.115*	0.118*
	(2.32)	(2.03)	(1.70)	(1.96)
LnALL_Training	0.056	-0.035	0.215	0.116
	(0.54)	(-0.30)	(1.63)	(0.98)
SocialSupport	0.038*	0.045**	0.044*	0.029
	(2.01)	(2.19)	(1.83)	(1.36)
CISA	0.168	0.202	0.060	0.149
	(0.81)	(0.90)	(0.23)	(0.64)
Gender	0.216	0.226	0.025	0.233
	(1.30)	(1.24)	(0.12)	(1.25)
CPA_CIA	-0.271	-0.249	0.041	-0.332
	(-1.46)	(-1.23)	(0.18)	(-1.60)
LnTenure	0.218*	0.020	0.129	0.449***
	(1.77)	(0.15)	(0.83)	(3.26)
Constant	-0.878	-0.624	-1.366	-0.974
	(-0.68)	(-0.44)	(-0.84)	(-0.67)
N	45	45	45	45
R2	0.45	0.31	0.42	0.51
Adj_R2	0.34	0.18	0.31	0.41

TABLE 4 (continued)

Panel B: Data Analytics Use for Communication

	(1) ***Overall_ Performance*** ***Coeff*** ***(t-stat)***	**(2)** ***Internal_Audit_ Performance*** ***Coeff*** ***(t-stat)***	**(3)** ***Communication_ Performance*** ***Coeff*** ***(t-stat)***	**(4)** ***Business_Knowledge_ Performance*** ***Coeff*** ***(t-stat)***
DAUse_Communication	0.126**	0.122**	0.181***	0.099
	(2.30)	(2.03)	(2.78)	(1.59)
LnALL_Training	0.075	-0.017	0.237*	0.132
	(0.72)	(-0.15)	(1.90)	(1.11)
SocialSupport	0.034*	0.042*	0.036	0.026
	(1.79)	(1.99)	(1.60)	(1.21)
CISA	0.197	0.230	0.042	0.191
	(0.96)	(1.03)	(0.17)	(0.82)
Gender	0.187	0.197	-0.009	0.207
	(1.13)	(1.09)	(-0.04)	(1.10)
CPA_CIA	-0.231	-0.212	0.070	-0.292
	(-1.26)	(-1.05)	(0.32)	(-1.39)
LnTenure	0.211*	0.014	0.134	0.439***
	(1.72)	(0.10)	(0.92)	(3.14)
Constant	-0.686	-0.439	-1.122	-0.813
	(-0.53)	(-0.31)	(-0.73)	(-0.55)
N	45	45	45	45
R2	0.45	0.31	0.49	0.49
Adj_R2	0.34	0.18	0.39	0.40

TABLE 4 (continued)

Panel C: Data Analytics Use for Risks and Controls

	(1) ***Overall_ Performance*** ***Coeff*** ***(t-stat)***	**(2)** ***Internal_Audit_ Performance*** ***Coeff*** ***(t-stat)***	**(3)** ***Communication_ Performance*** ***Coeff*** ***(t-stat)***	**(4)** ***Business_Knowledge_ Performance*** ***Coeff*** ***(t-stat)***
DAUse_Risks_&_Controls	0.170***	0.164***	0.201***	0.150**
	(3.21)	(2.80)	(3.07)	(2.45)
LnALL_Training	0.095	0.002	0.258**	0.150
	(0.95)	(0.02)	(2.10)	(1.31)
SocialSupport	0.028	0.035*	0.030	0.020
	(1.50)	(1.74)	(1.34)	(0.94)
CISA	0.171	0.205	0.034	0.160
	(0.88)	(0.96)	(0.14)	(0.72)
Gender	0.190	0.200	-0.002	0.209
	(1.21)	(1.15)	(-0.01)	(1.15)
CPA_CIA	-0.325*	-0.302	-0.037	-0.376*
	(-1.83)	(-1.54)	(-0.17)	(-1.84)
LnTenure	0.268**	0.069	0.195	0.491***
	(2.26)	(0.52)	(1.34)	(3.60)
Constant	-0.456	-0.218	-0.884	-0.598
	(-0.37)	(-0.16)	(-0.58)	(-0.42)
N	45	45	45	45
R2	0.51	0.37	0.50	0.53
Adj_R2	0.41	0.25	0.41	0.44

TABLE 4 (continued)

Panel D: Data Analytics Use for Business Control Objectives				
	(1) ***Overall_ Performance***	**(2)** ***Internal_Audit_ Performance***	**(3)** ***Communication_ Performance***	**(4)** ***Business_Knowledge_ Performance***
	Coeff (t-stat)	***Coeff (t-stat)***	***Coeff (t-stat)***	***Coeff (t-stat)***
DAUse_Bus_Control_Objectives	0.129**	0.119**	0.150**	0.119**
	(2.54)	(2.15)	(2.41)	(2.09)
LnALL_Training	0.070	-0.022	0.229*	0.129
	(0.68)	(-0.19)	(1.79)	(1.10)
SocialSupport	0.035*	0.043**	0.040*	0.026
	(1.88)	(2.07)	(1.71)	(1.24)
CISA	0.185	0.222	0.052	0.168
	(0.92)	(1.00)	(0.21)	(0.74)
Gender	0.214	0.223	0.026	0.230
	(1.30)	(1.24)	(0.13)	(1.25)
CPA_CIA	-0.249	-0.228	0.053	-0.311
	(-1.37)	(-1.14)	(0.24)	(-1.51)
LnTenure	0.205*	0.008	0.121	0.437***
	(1.70)	(0.06)	(0.81)	(3.20)
Constant	-0.732	-0.486	-1.210	-0.837
	(-0.57)	(-0.35)	(-0.77)	(-0.58)
N	45	45	45	45
R2	0.46	0.32	0.46	0.51
Adj_R2	0.36	0.19	0.36	0.42

This table presents the results for the association between the use of data analytics and Internal_Audit_Performance. The dependent variable is internal auditor performance, measured by *Overall_Performance*, *Internal_Audit_Performance*, *Communication_Performance*, and *Business_Knowledge_Performance*. The independent variables are the internal auditor level of data analytics in different areas: continuous auditing *(DAUse_Continuous_Auditing)*, communication *(DAUse_Communication)*, risk and controls *(DAUse_Risks_&_Controls)* and align data analytics with business control objectives *(DAUse_Bus_Control_Objectives)*. Panel A presents the results for the association between *DAUse_Continuous_Auditing* and internal auditor performance measures. Panel B presents the results for the association between *DAUse_Communication* and internal auditor performance measures. Panel C presents the results for the association between *DAUse_Risks_&_Controls* and internal auditor performance measures. Panel D presents the results for the association between *DAUse_Bus_Control_Objectives* and internal auditor performance measures. All variables are winsorized at 1% and 99%. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.