Three Studies Examining Auditors' Use of Data Analytics

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THREE STUDIES EXAMINING AUDITORS' USE OF DATA ANALYTICS

by

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ABSTRACT

This dissertation comprises three studies, one qualitative and two experimental, that center on auditor's use of data analytics. Data analytics hold the potential for auditors to reallocate time spent on labor intensive tasks to judgment intensive tasks (Brown-Liburd et al. 2015), ultimately improving audit quality (Raphael 2017). Yet the availability of these tools does not guarantee that auditors will incorporate the data analytics into their judgments (Davis et al. 1989; Venkatesh et al. 2003).

The first study investigates implications of using data analytics to structure the audit process for nonprofessionalized auditors. As the public accounting profession continues down a path of de-professionalization (Dirsmith et al. 2015), data analytics may increasingly be used as a control mechanism for guiding nonprofessionalized auditors' work tasks. Results of this study highlight negative ramifications of using nonprofessionalized auditors in a critical audit setting. The second study examines how different types of data analytics impact auditors' judgments. This study demonstrates the joint impact that the type of data analytical model and type of data analyzed have on auditors' judgments. This study contributes to the literature and practice by demonstrating that data analytics do not uniformly impact auditors' judgments. The third study examines how auditors' reliance on data analytics is impacted by the presentation source and level of risk identified. This study provide insights into the effectiveness of public accounting firms' development of data scientist groups to incorporate the data analytic skillset into audit teams.

Collectively, these studies contribute to the literature by providing evidence on auditors' use of data analytics. Currently, the literature is limited to demonstrating that auditors are not effective at identifying patterns in data analytics visualizations when viewed before traditional

audit evidence (Rose et al. 2017). The three studies in this dissertation highlight that not all data analytics influence judgments equally.

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GENERAL INTRODUCTION

Advances in technology have expanded data analysis capabilities to be incorporated into the audit process (Brown-Liburd et al. 2015). These data analytics include testing performed by traditional analytical procedures (Appelbaum et al. 2017; Titera 2013) and have expanded to include methods such as population testing (Kogan et al. 2014; Raphael 2017), predictive modeling (Kuenkaikaew and Vasarhelyi 2013; Krahel and Titera 2015) and unstructured data analysis (Warren et al. 2015; IAASB 2017). Prior research on auditor's use of data analytics is limited to showing that they are not effective at identifying patterns in data analytics visualizations when viewed before traditional audit evidence (Rose et al. 2017).

Despite the advances in technology and the increased ability to identify relevant information, auditors may be reluctant to rely on such tools, even when deemed 100% accurate (Sutton et al. 1995). Thus, the potential usefulness of these tools may be constrained by the human users (Alles and Gray 2015), and decisions will be unaffected if the decision maker refuses to use these tools (Davis et al. 1989; Venkatesh et al. 2003). Interest to expand the use of data analytics into the audit process is evidenced by the development of an Audit Data Analytics Guide by the AICPA's Assurance Services Executive Committee (ASEC) (AICPA 2017), the formation of a Data Analytics Working Group by the IAASB (IAASB 2017), and a PCAOB board member declaring their encouragement to use and expectation for these tools to improve audit quality (PCAOB 2016). Thus, while data analytics are expected to play a more pronounced role in the audit process, it is unclear if auditors will effectively use these tools, and audit quality will ultimately improve.

This dissertation comprises of three separate studies, one qualitative and two experimental, examining the use of data analytics in the audit process. The first study investigates the implications of using data analytics to structure the audit process for nonprofessionalized auditors[1]. This study demonstrates the importance of using professionalized auditors to perform follow up audit procedures on risks identified by data analytics. The second study examines data analytics in the financial statement audit context by demonstrating how different data analytical models that analyze different types of data impact auditors' judgments. The third study highlights the implications of presenting the findings of data analytics to external financial statement auditors from different sources under varying levels of risk. The following subsections provide additional detail on each chapter by highlighting the motivation for each study, the research method employed, and the contributions of each study to the accounting literature. The overall contribution of this dissertation is summarized in the last section.

Study One: Consequences of Deprofessionalization: The Use of Data Analytics to Guide Nonprofessionalized Auditors

The first study examines an attempt to structure the audit process using data analytics to guide the work of nonprofessionalized auditors in a critical audit context. Since the 1970's the public accounting professional has undergone several changes, including loss of the power to self-regulate (embodied by the creation of the PCAOB) and delivering increasingly commodified audit procedures (Dirsmith et al. 2015). Two distinct camps exist regarding the view of professions. While the first camp views professions as shifting from an economically disinterested expert to an

[1] The terminology nonprofessionalized auditors refers to contract workers who are hired to perform audit services but are not required to go through a specified educational training, apprenticeship, and licensure process that is typical of the professionals, including the financial audit profession.

entrepreneur (Abbott 1988; Reed 1996), the other camp views professions as engaging in commercialization tactics in an attempt to reclaim their service ideal (Dirsmith et al. 2015). Arguably, the public accounting profession is continuing down a path of de-professionalization (Dirsmith et al. 2015), so it is important to understand the implications of using nonprofessionalized auditors in a critical audit context. The ability of technology enabled tools, such as data analytics, to structure the audit process (Dowling and Leech 2014) calls into question the necessity of public accounting firms to utilize professional auditors to the extent currently done. Regulators may need to reconsider whether the audit profession should maintain its monopoly over the performance of certain types of audits.

To examine the use of hiring nonprofessionalized auditors to work in a critical audit setting, a group of healthcare regulatory fraud auditors called Zone Program Integrity Contractors (ZPICs) were examined. Several characteristics of the ZPIC auditors were identified as violating the criteria of an established profession. Although there are multiple frameworks for defining what constitutes a profession, generally professions meet four criteria. First, professions hold a unique set of knowledge and expertise and employ this expertise (Kultgen 1988; Covaleski et al. 2003) to symbolize power and control over a domain (Blackler et al. 1993). Second, the unique knowledge and expertise must enable the professional to make decisions that cannot be preprogrammed and to apply rules that cannot be entirely codified (Larson 1977). Third, professionals must hold a credential to certify their expertise and engage in continuing education (Kimball 1995). A fourth requirement is that professions must serve and support the public interest and not engage in self-interested behavior (Kultgen 1988; Fogarty et al. 2006). The results of this dissertation study indicate that ZPIC auditors fail to meet these four criteria of a profession.

Data was collected primarily through reviewing publicly available documents discussing the ZPIC auditors coupled with interviews of ZPIC auditees. While Reports to Congress highlighted purported benefits of the ZPICs audit activity, practitioner sources suggested there were drawbacks (Vishnevetsky 2012; Van Halem et al. 2012; Baucus et al. 2013; DHHS 2012; DHHS 2014; DHHS 2015). In total, 36 semi-structured interviews were conducted with individuals employed by healthcare providers subject to ZPIC audit. Interview data was triangulated with archival documents provided by participants and publicly available information (such as from government agencies including the Office of Inspector General) to enhance the validity of the findings. The results of this study highlight several consequences of empowering nonprofessionalized auditors in a critical audit setting. These results highlight that the mere availability of data analytic tools is insufficient to improve decision making. Several opportunities for improvement of data analytics are highlighted including ensuring that users have an appropriate level of power, ensuring that employers maintain a properly designed incentive structure, and ensuring that users have adequate training to understand the implications of false positives.

This study demonstrates that using nonprofessionalized auditors to audit accounts and transactions identified by a data analytic tool as high risk may have unintended consequences, including potentially negative societal implications. The study raises concerns over whether the deprofessionalization of the audit profession and allowing auditors not a part of the profession to conduct audits may not be in the public interest.

Study Two: The Impact of Data Analytics on Auditors' Judgments and Decisions

Study Two examines the impact of different data analytical models that analyze different types of data has on auditors' judgments.

Prior accounting research focuses on the capabilities and benefits of data analytics (Jans et al. 2014; Kogan et al. 2014). Research examining auditors' use of data analytics is limited to demonstrating that they are not effective at identifying patterns in visualizations when viewed before traditional audit evidence (Rose et al. 2017). With the expansion of the data analytical tools (Brown-Liburd et al. 2015), it is unclear if auditors will use these tools uniformly. Research has shown that even when decision aiding tools are deemed to be 100% accurate, auditors are still reluctant to rely on these tools (Sutton et al. 1995). Accordingly, this study seeks to address the gap in the literature by investigating whether the type of data analytical model and data analyzed impacts auditors' judgments.

Drawing upon the theory of cognitive fit, this study hypothesizes that auditor's judgments will be impacted more by anomaly data analytical models and data analytics that analyzed financial data. Cognitive fit occurs when there is congruence between the method or process used by a decision maker and a decision facilitating tool (Vessey and Galletta 1991; Arnold and Sutton 1998; Al-Natour et al. 2008). Cognitive fit increases with a decision makers experience using a decision aiding tool (Goodhue and Thompson 1995; Dunn and Grabski 2001). Auditors' use of analytical procedures tends to focus on simpler versions of anomaly models (Hirst and Koonce 1996; Brewster 2011; Brazel et al. 2014), and research and practitioner literature suggests that auditors' use of predictive models is limited. Thus, auditors are expected to experience higher cognitive fit when using anomaly models than predictive models, resulting in anomaly models causing a greater change in judgments. As auditors are less experienced and less effective at using nonfinancial data compared to financial data (Cohen et al. 2000; Brazel et al. 2009; Brazel et al. 2014), auditors are expected to experience higher cognitive fit when using data analytics that analyzed financial data, resulting in a greater change in judgments.

An experiment utilizing a 2 x 2 experimental design was conducted. The experiment involved external financial statement auditors making judgments related to a potential risk identified by their firm's central data analytics group. Specifically, participants made judgments relating to reliance, fraud risk assessments, and budgeted audit hours. The two independent variables for the experiment are the type of data analytical model used (anomaly vs. predictive) and type of data analyzed (financial vs. nonfinancial). Although the same risk was presented from the central data analytics group, the underlying analysis used to identify the risk was manipulated. The experiment manipulates the type of data analytical model used by describing the central data analytics groups as using either anomaly or predictive models. Furthermore, the type of data analyzed was manipulated by informing participants that the anomaly or predictive models analyzed either journal entries (financial data) or e-mail language (nonfinancial data).

The results of this study suggest that while the type of data analytical model used and type of data analyzed do not result in different reliance and fraud risk assessments, their combined effect impacts budgeted audit hours. The change in budgeted audit hours resulting from a risk identified by data analytical model is contingent upon the type of data that is analyzed. Specifically, when predictive models are used, auditors increase budgeted audit hours more when financial data is analyzed as compared to nonfinancial data. The opposite is true for anomaly models, such that auditors increase budgeted audit hours more when nonfinancial data is analyzed as compared to financial data.

This study illustrates the joint effect of the type of data analytical models used and type of data analyzed on auditors' judgments with regard to budgeted audit hours. This study provides initial experimental evidence on the impact of different types of data analytics impacting auditors' judgments. The results highlight the importance of considering joint effects of the impact of data analytics on auditors' decisions.

Study Three: The Impact of the Human Factor on Auditors' Reliance on Data Analytics

Study Three applies the theory of Trust to auditors' use of data analytics and explores auditors' reliance on data analytics based on the effect of the presentation source of the findings and level of risk identified. Data analytics may be viewed as an outgrowth and expansion of analytical procedures (Appelbaum et al. 2017). While traditional audit teams have possessed the necessary skillset to perform analytical procedures (Hirst and Koonce 1996; Trompeter and Wright 2010), the advanced capabilities of data analytics requires different technical skills to be acquired by audit teams (Richins et al. 2017). To implement this skillset, audit teams can consult with data scientists or use their firm's data analytical software (Ernst and Young 2015a; Agnew 2016a; Richins et al. 2017). These two methods may not be relied on uniformly, as individuals may be reluctant to rely on, and less trusting of technology to perform functions as compared to other humans (Waern and Ramberg 1996; Lewandowsky et al. 2000). Auditors are more likely to rely on information that requires a simple course of follow up action (Glover et al. 2005). Yet, decision makers trust information provided by other humans more consistently, such as under varying levels of risk, than information provided by a system. Thus, developing and leveraging data scientist groups may be effective at inducing reliance on data analytics for a variety of circumstances.

Drawing upon the theory of Trust, this study hypothesizes that auditor's reliance on data analytics will be greater when results are presented from a data scientist and a low level of risk is identified. Trust refers to "The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor...” (Mayer et al. 1995, pg. 712). Decision makers trust information provided by another human more than technology enabled systems (Lewandowsky et al. 2000), and this trust increases reliance (Muir 1989; Lerch and Prietula 1989). Thus, auditors are predicted to rely more on information provided by another human as compared to a system. Additionally, when audit evidence suggests a high risk, auditors rely less on this information at is requires a complex subsequent course of action (Glover et al. 2005). Thus, auditors are predicted to rely more on information that presents a low audit risk than a high audit risk. As prior research indicates that decision makers rely more consistently on information provided by humans than systems (Lewandowsky et al. 2000), when the results of data analytics identifying a high risk is presented by a system it is expected to result in a greater decrease in reliance than when presented by another human. Thus, this study predicts that the level of risk identified will moderate the effect of presentation source on auditors’ reliance on data analytics.

For this study, an experiment using a 2 x 2 design was conducted. The experiment involved external financial statement auditors determining how likely they are to rely on the findings of data analytics. The two independent variables for the experiment is the presentation source (another human vs. a self-generating system) and the level of audit risk identified (high vs. low). The experiment presents participants with a report of the findings of data analytics, however the presentation source and the information content of the report is manipulated. Participants were informed that the output report of the data analytics was either presented from their firms’ data scientist, or was shown on their computer using the data analytics software. Participants were informed that the results of the data analytics suggested either a high or low audit risk.

The results of this study show that auditors’ reliance on data analytics do not differ as a result of a different presentation source or level of risk identified. Although the predicted moderation of level of risk identified on presentation source was not observed, examining the joint effect of these two variables on reliance presented an unexpected finding. The level of risk identified and presentation source have a joint impact on auditors' reliance on data analytics. When the results of the data analytics are presented from a self-generating system, auditors are more likely to rely on a high risk than a low risk. The opposite is true when the results of data analytics are presented from another human, as under these circumstances auditors are more likely to rely on a low risk as compared to a high risk.

The results of this study suggest that developing and leveraging data scientist groups may not be the most effective manner for firms to induce auditors' reliance on data analytics that identify high risk audit areas. While identifying low risk audit areas may aid in performing more effective audits, data analytics may be used to facilitate auditors focusing their time on more high risk, judgment intensive tasks (Brown-Liburd et al. 2015). The results of this study suggest that the approach used by the firms of developing data scientist groups to aid in data analysis results in a reluctance of relying on high risk information when presented by another human. Thus, firms should reevaluate the effectiveness of their approach of developing data scientists groups to implement data analytics into the audit process.

Overall Contribution

Accounting firms have increased their use of data analytics (Deloitte 2010; AICPA 2015; Coffey 2015; Ernst and Young 2015). Prior research examining auditors' use of data analytics has indicated that auditors are not particularly effective at identifying patterns of data analytic visualization when viewed prior to traditional audit evidence (Rose et al. 2017). The three studies reported in this dissertation seek to extend and contribute to the data analytics literature and are centered on auditors' use of data analytics. Combined, these three studies aim to demonstrate the need for professional auditors to perform follow up audit work after data analytics identify a potential risk (Study One) and shows that even when presenting the same results, the underlying method used by the data analytics and presentation of the output of the data analytics impacts auditors' judgments under some circumstances (Study Two and Study Three).

Results from Study Two and Study Three support the notion that data analytics impact auditors' judgments. Although both studies focus on auditors' judgments using data analytics, the focus of these studies are quite different. The focus of Study Two is on the new forms of data analysis arising from advancements in technology (Brown-Liburd et al. 2015). A variety of other types of data analyses could have been explored that present opportunities for future research. In contrast, Study Three focuses on the effectiveness of including data scientists into the audit team in order to induce auditors' reliance on the findings of data analytics. The results of Study Three highlight that there is a joint effect of the presentation source and the level of identified risk.
Collectively, these studies contribute to the literature by demonstrating that the mere availably of data analytics is insufficient to uniformly change auditors' judgments. Different types of data analytics may result in different judgments. These studies provide initial experimental support for the impact of data analytics on auditors' judgments. They highlight the need to investigate previously unexplained phenomena within this emerging domain.

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STUDY ONE: CONSEQUENCES OF DEPROFESSIONALIZATION: THE USE OF DATA ANALYTICS TO GUIDE NONPROFESSIONALIZED AUDITORS

Introduction

Certain factors call into question if the public accounting profession is still truly representative of a profession. Although a fundamental aspect of professions is that they are self-regulating (Kimball 1995), the downfall of Arthur Andersen resulted in the passage of SOX and the creation of the PCAOB to regulate the public accounting profession. Additionally, increased audit market competition has created continuous pressure to lower audit fees (Dirsmith et al. 2015), calling into question the long term profitability and viability of the auditing profession. In response to pressure to decrease audit fees, audit procedures are often standardized. Such standardization results in increasing automation and decreasing professional judgment required of auditors. This commodification of audit procedures compels commercialization practices (Dirsmith et al. 2015) and has resulted in auditors expanding the types of auditing services provided (Gendron and Barrett 2004; O'Dwyer 2011; Suddaby et al. 2009). Such commercialization practices raise questions as to whether the auditing profession is truly a profession seeking to serve society, or merely purporting to serve society as justification for engaging in profit seeking endeavors (Wyatt 2004).

Two distinct camps exist regarding perceptions of professionalism as it relates to commercialization (Dirsmith et al. 2015). The first camp views professionals as shifting from an economically disinterested expert to an organization-based knowledge worker or entrepreneur (Abbott 1988; Reed 1996). For many years professions, such as public accounting, gained social status and authority by providing an expert service to society (Merton 1968), while striving to achieve a “service ideal” for clients (Larson 1977). Although professions may claim to serve the needs of society, this claim may truly represent serving the vested interests of the profession rather than society (Larson 1977). Such claims may be attributable to shifts in societal values emphasizing performance and outcomes regardless of the underlying processes (Krause 1994). Professionals moving away from self-seeking knowledge workers and toward commercialization / commodification practices may result in the “death of the professions” (Krause 1994; Brint 1994). The second camp views professionals as seeking to reclaim their service ideal (Dirsmith et al. 2015). This camp views the expansion of non-certified numbers expanding the need for auditing (Power 1999), which increases the need for services and professionalism among accountants. This camp views the right to serve clients as highlighting their professional endeavor (Dirsmith et al. 2015). This camp views commercialization of assurance (Gendron and Barrett 2004; O’Dwyer 2011; Suddaby et al. 2009), and consulting services (Suddaby et al. 2007), as accountants and public accounting firms using their expertise to provide additional necessary services to society. Yet it is unclear which of the two camps best explains the commercialization of auditing on the accounting profession and the implications of using nonprofessionalized auditors in a professional audit context. The lingering question is whether we would be better off eliminating the profession and its monopoly over audit services, and simply recognizing it as an industry where competition can produce similar results at less cost in the absence of monopoly rents.

The purpose of this study is to examine the impact of using nonprofessionalized auditors in a critical audit context. Specifically, this study examines a unique setting where the U.S. federal government is leveraging data analytics to structure the audit process for nonprofessionalized auditors. Technology enabled tools, such as data analytics, can be used to control, facilitate, and support audit work (Winograd et al. 2000; Banker et al. 2002; Dowling and Leech 2007). These tools may be used to standardize the audit process and restrict the auditor's ability to exercise professional judgment and ensure that intended audit procedures are followed (Dowling and Leech 2014; Westermann et al. 2015). This automation may enable professionals to disseminate knowledge to nonprofessionals during the audit process and decrease the need of professionals. Yet, using such technologies may have adverse implications on the users, such as failing to consider issues beyond what was identified by the technology (Seow 2011).

A component of the U.S. Small Business Jobs Act of 2010 required the Center for Medicare and Medicaid Services (CMS) to implement a data analytic tool called the Fraud Prevention System (FPS) to help identify Medicare fraud. Several well known contractors including Verizon, Northrop Grumman and IBM aided CMS in developing and implementing the FPS, providing legitimization to the new FPS (DHHS 2012). Subsequent to the FPS identifying an outlier, an outsourced contractor called a Zone Program Integrity Contractor (ZPIC) is assigned the task of performing a forensic audit of the outlier, as well as investigating the auditee for any overall pattern of fraudulent claims. Although the ZPIC firms are encouraged to employ professionals (CMS 2007), the results of this study highlight the extensive use of nonprofessionals by the ZPIC firms to perform audit work.

To examine the impact of using nonprofessionalized auditors, data was primarily collected through reviewing public documents discussing the ZPIC auditors' performance and interviews of ZPIC auditees. While Reports to Congress highlighted the benefits of ZPIC audit activity, practitioner articles highlighted several drawbacks (Vishnevetsky 2012; Van Halem et al. 2012; DHHS 2012; DHHS 2014; DHHS 2015b; Baucus et al. 2013). Interviewing auditees allowed the researcher to identify both benefits and drawbacks arising from ZPIC audit activity. Additionally, interviewing participants on their relationships with other regulatory auditors and financial statement auditors allowed the researcher to assess the congruence of perceptions related to ZPIC auditors and whether these perceptions were attributable to the form of oversight or to differences in the ZPICs' audit tactics.

Thirty-six semi-structured interviews were conducted with individuals employed by providers subject to ZPIC audit. Interview data was triangulated with archival documents from participants and publicly available information from government agencies (i.e., Office of Inspector General) and practitioner websites (i.e., attorneys, CPAs, and consultants) in order to enhance the researcher's understanding of these audit relationships and to increase the validity and reliability of the data and analysis (Yin 2009).

This study contributes to the academic literature by illustrating the implications of utilizing nonprofessionals in an audit setting. The advancement of technology enables the standardization and commodification of auditing procedures, enabling commercialization (Dirsmith et al. 2015), and calling into question the necessity of professional auditors. Such commercialization opportunities expand auditors' jurisdiction, while impairing objectivity and independence (Wyatt 2004; Zeff 2003a; Zeff 2003b). As the public accounting profession is expressing increasing interest in using data analytics as part of the audit process (Appelbaum et al. 2017; Coffey 2015; AICPA 2017), this study highlights the importance of using professional, as compared to nonprofessionalized, auditors to audit identified anomalies even when using data analytics. Prior professionalism research has focused on what defines a profession (Kimball 1995; Kultgen 1988), or the challenges professions face regarding threatening forces and barriers to expansion (Dirsmith et al. 2015; Covaleski et al. 2003; Pentland 2000). Yet, there is a lack of research examining the regulatory auditors' claim to expertise in the public sector (Gendron et al. 2007) and the implications of nonprofessionalized auditors acting in a professional capacity (Suddaby et al. 2009). While utilizing outside contractors allows organizations to focus on core activities and avert costs such as training and recruitment (Covaleski et al. 2003; Matusik and Hill 1998), this study demonstrates adverse societal implications from utilizing nonprofessionalized auditors to guide and execute audits.

This study is very timely and important as the most recent Report to Congress published by DHHS and CMS indicates an intention to expand ZPIC jurisdiction to other U.S. governmental agencies (DHHS 2015c), specifically, Medicaid and the Children's Health Insurance Program (CHIP).[2] Evidence of ZPIC expansion to Medicaid is further demonstrated by the creation of Unified Program Integrity Contractors (UPICs) in 2016 that combines the work of the ZPIC auditors with their Medicaid counterparts. Although the findings in this study were confined to Medicare, the expansion of ZPIC jurisdiction suggests similar findings will follow in Medicaid. Overall, these activities provide substantial evidence of ZPIC auditors' jurisdiction expanding without consideration of the societal impact.

The remainder of this paper is organized into five sections. The next section provides background on the relevant academic literature. The following section discusses the method utilized in this study. The fourth section presents the findings of this study. The fifth section presents a discussion of the findings and the final section presents concluding remarks.

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[2] Medicare is a federal health insurance program in the U.S. for individuals over the age of 65, whereas Medicaid is a program that helps with medical costs for individuals with low incomes and limited resources (CMS 2000).

Professionalism

While multiple frameworks exist for defining what constitutes a profession, generally professions are considered to be defined by meeting four criteria. A profession must necessitate a unique set of knowledge and expertise and employ this expertise (Kultgen 1988; Covaleski et al. 2003) to symbolize power and control over a domain (Blackler et al. 1993). A second requirement is that this unique knowledge and expertise must enable the professional to make judgments that cannot be preprogrammed, that applies rules that cannot be entirely codified, and that allows the professional discretion to cope with unforeseen problems (Larson 1977). A third requirement is that professionals must hold a credential to certify their expertise (Kimball 1995), and that continuing education is prescribed to maintain this credential (Kultgen 1988). A fourth requirement is that a profession must serve and support the public interest and not engage in self-interested behavior (Kultgen 1988; Fogarty et al. 2006).

As the public accounting profession continues down a path of de-professionalization (Dirsmith et al. 2015), consideration should be given to the implications of displacing professionals to a non-professional environment. Moving from a profession-based environment into a nonprofessional work environment may change the core professional values (Suddaby et al. 2009). Nonprofessionals often do not understand or appreciate the importance of acting professional when conducting engagements (Suddaby et al. 2009). Problems arise when placing professionals in non-professional work environments (Aranya and Ferris 1984). Placing a professional in a nonprofessional work environment emphasizing efficiency and limiting individual discretion will erode the individual’s professional values and reputation over time (Scott 1966). When professionals are employed by professional service organizations, they are subject to socialization practices and disciplinary techniques to align their actions with organizational goals (Dirsmith et al. 1997; Covaleski et al. 1998), however these socialization practices and disciplinary techniques are less prevalent when working for non-professional service firms (Suddaby et al. 2009).

Knowledge and Expertise

Professionals must develop and hold a unique set of knowledge and expertise (Kultgen 1988; Covaleski et al. 2003). Knowledge using professional judgment creates a claim to expertise deserving recognition as a profession (Elliott 1999; Kultgen 1988). A profession is recognized by establishing dominance over competing knowledge bases and expertise (Abbott 1988; Covaleski et al. 2003). Claims to expertise are more persuasive when they are linked with objective facts (Latour 1987). As expertise is associated with performance (Bédard and Biggs 1991; Knapp and Knapp 2001; Knechel et al. 2013), professions are expected to report strong performance outcomes. Merely claiming this expertise can arguably be more effective than actually possessing this expertise (Alvesson 1993).

Professions often encounter substantial challenges that can be used to legitimize their expertise (Abbott 1988; Gendron et al. 2007; Gendron and Barrett 2004; Pentland 2000; Power 1999; Power 2003; Rittenberg and Covaleski 2001). During the emergence of a profession, constructing a need to be fulfilled is arguably more important than demonstrating technical abilities to fill that need (Van de Van and Garud 1993). Skilled use of language as a means of managing public impressions aids in legitimization (Ruef 2000; Suddaby and Greenwood 2005; Hopwood 2009). A profession may legitimize their expertise in a new domain by linking that domain to a domain where it already has established legitimacy (Latour 1987). Thus, legitimacy maintains a dominant order by enabling powerful actors to remain in power (Archel et al. 2011;

Suddaby et al. 2007). Efforts to enhance legitimacy include exploiting fears of others (Guénin-Paracini et al. 2014), and gaining recognition, such as by a government agency (Power 2013; Power 1997).

Legitimizing expertise can also be enabled by the use of technology, such as the ZPIC auditors' use of the FPS. Technology enabled tools may be used to justify decisions (Newell and Marabelli 2015), disseminate expertise, and structure tasks for lower level decision makers (Dowling and Leech 2014). Thus, demonstrating the expertise of the individuals that developed the technology may be adequate to legitimize the use of the technology. Technology may aid in legitimizing decision makers expertise by demonstrating the ability to identify highest risk areas in need of greatest investigation (DHHS 2012; DHHS 2014; DHHS 2015a). Gaining recognition by a government agency, such as CMS, legitimizes the use of technology (Power 2013; Power 1997).

Judgment and Decision Making

The second requirement of a profession is that the specialized knowledge held allows professionals to make judgments that cannot be preprogrammed or reduced to a set of rules, while allowing the professional autonomy to make decisions (Larson 1977; Abbott 1988). As professions advance, their expertise tends to become commodified allowing the unique knowledge to be translated into a set of rules resulting in a struggle for control of domains and markets. Building a claim to expertise is a continuous process (Gendron et al. 2007). The development and maintenance of abstract systems of knowledge used to establish their jurisdictions is crucial to the survival of professions (Abbott 1988). A profession's failure to develop new knowledge will result in individuals questioning if the work performed is truly representative of a profession. Once a domain is established, professions engage in commercialization tactics by using their abstract knowledge to develop new knowledge and expand their jurisdiction to new practice areas, ultimately annexing new areas in order to ensure survival (Abbott 1988; Dirsmith et al. 2015). Sites of ambiguity become opportunities for professions to expand their area of expertise and jurisdiction (Gendron et al. 2007). Thus professions may seek to highlight a need in order to fill that need, making their claim to expertise indispensable and enabling expansion of their jurisdiction (Courtois 2017; Callon 1986).

Although assurance services of accountants and public accounting firms have expanded (Gendron and Barrett 2004; O'Dwyer 2011; Suddaby et al. 2009) along with consulting services (Suddaby et al. 2007), this commercialization can be argued to be "out of control" (Gendron and Spira 2009). Although the field where an audit occurs may change, more activities are being made auditable, including environmental audits, educational audits, medical audits, energy audits and value for money audits (Pentland 2000). Although expanding auditing requirements is intended to result in increased accountability, increased accountability may not result in improved performance (Pentland 2000).

Certification

The third requirement of a profession noted above is having a credential certifying expertise in an area. Kimball (1995) discusses how the emergence of the modern professional is produced by several stages, concluding with obtaining a credential to certify expertise and formal learning. Among public accountants in the U.S., the CPA credential serves as symbolizing auditing expertise. Holding a credential helps legitimize the expertise required for professions (Reed 1996; Covaleski et al. 2003).

New discoveries or innovations create opportunities for professionals to undergo professional growth by gaining an understanding of these developments (Abbott 1988). For professionals to ensure that their domain specific knowledge or expertise stays current in light of environmental changes, they utilize continuing education (i.e., CPE courses) (Kultgen 1988). Changing environmental factors require professionals to continuously "reeducate" themselves in response to even incremental developments (Abbott 1988). This continuous education requires an ongoing effort from professionals to ensure that their domain specific knowledge remains current (Abbott 1988).

Focus on Public Interest

The fourth requirement of a profession noted above is that professions seek to develop new services to address societal issues, while refusing to engage in self-interested behavior (Abbott 1988; Kultgen 1988; Fogarty et al. 2006). Professionals seek to serve the public while simultaneously safeguarding their jurisdiction against competing professions (Abbott 1988; Cooper and Robson 2006). Despite the importance of a professional serving the public interest, public accountants may be more concerned with serving the client than serving the public interest (Cooper and Robson 2006).

Although public accounting firms have the expertise to certify numbers (Power 1999), some have argued that the portfolio of services delivered are expanding too rapidly (Gendron and Spira 2009). Thus, it is unclear if the additional services delivered to the public by the public accounting profession are truly in the public interest, or merely an attempt by firms to maximize profitability at the public's expense. Although public accounting firms currently have a monopoly over providing financial statement auditing services, this monopoly could be withdrawn if regulators no longer felt the profession's members were serving the public interest. Eliminating the public accounting firms monopoly would potentially allow competition that may produce similar results without the excess costs of monopoly rents accrued by the profession.

Research Method

Setting

Section 4241 of the U.S. Small Business Jobs Act of 2010 required CMS to implement the Fraud Prevention System (FPS), a data analytic tool to help identify Medicare fraud. Such government initiatives are commonly used in an attempt to constrain costs (Chua 1995; Samuel et al. 2005). The motivation behind the development of this tool demonstrates how technology can be used as a component of a broader initiative (Preston et al. 1992; Power 1997; Ogden 1997), in this case to purportedly fight healthcare fraud.[3] This new tool was implemented on June 30, 2011 (DHHS 2012). To assist in conducting on-site audits of possible fraudulent activity identified by the FPS, CMS outsourced audit responsibilities to ZPIC firms (CMS 2007).[4] Subsequent to CMS performing data analysis by using the analytics discussed above and

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[3] Within the healthcare industry in the U.S., revenue is generated by providing services, then potential payers such as health insurance providers (e.g., United Healthcare) or government programs (e.g., Medicare) are billed so that the provider can be reimbursed for services provided. Per USC 18 **§** 1347, Healthcare fraud is defined in the U.S. as:
(a) Whoever knowingly and willfully executes, or attempts to execute, a scheme or artifice—
(1) to defraud any health care benefit program; or
(2) to obtain, by means of false or fraudulent pretenses, representations, or promises, any of the money or property owned by, or under the custody or control of, any health care benefit program, in connection with the delivery of or payment for health care benefits, items, or services, shall be fined under this title or imprisoned not more than 10 years, or both. If the violation results in serious bodily injury (as defined in section 1365 of this title), such person shall be fined under this title or imprisoned not more than 20 years, or both; and if the violation results in death, such person shall be fined under this title, or imprisoned for any term of years or for life, or both.
(b) With respect to violations of this section, a person need not have actual knowledge of this section or specific intent to commit a violation of this section.

[4] The ZPICs replaced Program Safeguard Contractors (PSCs) subsequent to the PSCs being criticized by OIG for opening an insufficient number of new audits and ineffective data analysis (OIG 2007).

identifying an outlier, a ZPIC firm is assigned the role of auditing the outlier for possible fraud (DHHS 2012). ZPIC auditors are the primary users of the FPS (DHHS 2015a). Four full years of operations have now been reported, and implementation has been described as a success based on reporting of an increasing Return on Investment of 3.3:1 in 2012, 5:1 in 2013, 10:1 in 2014 and 11.5:1 in 2015 (DHHS 2012; DHHS 2014; DHHS 2015b; CMS 2015).[5] This impression of perceived success has created a desire to expand similar analytic tools to other government programs, specifically Medicaid and CHIP (DHHS 2015c). Despite the increasing ROI, Reports to Congress do not discuss factors such as access to care and changes to the quality of care at providers undergoing ZPIC audit. Further, the reported ROI is based on projected fraud collections and not actual realization.

As the ZPIC auditors are focused within the healthcare industry, it is important to understand industry specific issues related to healthcare fraud. In addition to fraud, abusive and wasteful practices are also of major societal concern. The distinction between fraud, abuse and waste is often difficult to delineate. Fraudulent activities include billing for services that are not provided to patients or services that are provided but unnecessary. Abusive practices are viewed as borderline fraudulent, for example prescribing multiple doctor visits to a single patient when one is sufficient. The distinction between abuse and fraud relates to motivation of the provider, such that if there was an expectation for at least a marginally better medical result, then it is abusive and not fraudulent. Waste is defined as a service that passes neither a cost-effective test nor a cost-benefit test. Wasteful procedures are often performed as a pre-emptive defense mechanism by physicians against malpractice litigation, and may include duplication of

[5] Return on Investment is calculated based on Total Estimated Savings (Actual Savings plus Projected Savings) divided by Total estimated Costs (Development Contractor Costs, Modeling Costs, Employee salaries and benefits, and Investigation costs) (DHHS 2012; DHHS 2014; DHHS 2015b; CMS 2015).

procedures (Mashaw and Marmor 1994). Although decreasing the instances of fraud is of primary concern, reducing the amount of abuse and waste are potential added benefits of ZPIC audit activity.

ZPIC auditors may conduct an on-site audit without giving the auditee prior notice, reducing the opportunity for an auditee to alter or destroy incriminating evidence. Four different ZPIC firms cover seven different geographic zones, including nine designated "hot-spots" (DHHS 2012). ZPIC auditors' compensation changed fairly recently from being based on cost reimbursement (DHHS 2012; DHHS 2014) to being based on the amount of savings (fraud dollars) reported (DHHS 2015c). ZPIC firms are paid by and report to CMS.

The ZPIC auditors have the ability to recommend suspension of Medicare payment that, if accepted, results in eliminating cash flow derived from Medicare services rendered. Due to the results of ZPIC Medicare audit activity discussed in Reports to Congress (DHHS 2012; DHHS 2014), sub-contractor audit activity has expanded to Medicaid (DHHS 2015b) and thus far the one contract awarded for a specific jurisdiction was awarded to a former ZPIC firm (CMS 2016a).

Data collection

Sutton et al. (2011) discuss how the use of qualitative methods is often preferable as a research method for examining emerging phenomena. An example of such emerging phenomena is the implications of using nonprofessionalized auditors in audit settings. As organizations may report different experiences from ZPIC audits and prepare and respond differently, a cross-sectional field study was selected for this study (Lillis and Mundy 2005).

Semi-structured interviews were utilized as they allow for data collection on topics of interest (identified by the process below); however, these interviews also permit the interviewer to adjust as appropriate to explore new insights that present themselves. The five components of research design outlined by Yin (2009) were followed. Consistent with Yin (2009), the researcher first identified the primary research question, “why are ZPIC auditors so successful as reported to Congress and how are data analytics contributing to this success?” (As new insights presented themselves, this question began to evolve as success might not really be success, and data analytics might not really be beneficial to achieving real success). The second component is to identify propositions, however as this study is exploratory, propositions are not necessary (Yin 2009). Third, the unit of analysis was determined; in this study the unit of analysis was ZPIC audit activities and execution. The fourth component identifies the analysis (see the “data analysis” section below). In order to ensure the validity in the interpretation of findings, the final component of research design (Yin 2009), the researcher sought any instances contrary to the primary findings.

To develop the protocol, as the ZPIC auditors are concerned with regulatory compliance, first previous literature was reviewed to determine which factors have been shown to increase regulatory compliance, such as increased oversight (Hoopes et al. 2012; Atwood et al. 2012). The researcher then developed a series of questions with the input of a partner, a manager and a senior in the healthcare practice of a national accounting firm, a member of the AICPA’s Health Care expert panel, two auditing professors, as well as three former external financial statement auditors. Figure 1 provides the interview protocol.[6]

Contact with healthcare providers subject to ZPIC audit was established through various sources including an accounting firm, state and sub-industry healthcare organizations and

[6] Additional questions in the “Societal Impact” section were added to the protocol after the 24th interview.

conferences, articles in publicly available sources, consultants and attorneys. Employees of several providers were then interviewed regarding the ZPIC audit process. In total, thirty-six individuals from across the U.S. were interviewed. The interviews were subsequently transcribed by the researcher.

Most of the interviews were conducted with C-level executives (or other top-management personnel equivalent) or owners of healthcare providers. The remaining interviews were with two administrators (similar to office managers), a consultant, two directors, a manager and other high ranking clinical personnel.[7] Participants located in six of the seven geographic zones have been interviewed covering audits by three of the four ZPIC firms. Thirty-six percent of the participants were located in a designated hot spot region. Sixty-seven percent of participants had an on-site visit from the ZPIC auditors. There were seven different types of healthcare providers included in the sample.[8] Twenty-two percent of the participants were employed by not-for-profit organizations. Seventeen participants worked for small organizations or organizations with significant family involvement; thus, interviewing these participants addresses a concern of prior research that small organizations are not always adequately represented in healthcare academic research (Marmor and Morone 2005). Overall, there is substantial diversity among the participants. No significant differences were noted attributable to different sub-groups (i.e., industry type or location). Table 1 provides complete demographic information.

The interviews lasted from 31 to 104 minutes and took place from March 2015 through April 2017. The interviews were conducted in the participants' office, over the phone, or in a public location. Participants were provided with broad topics that would be covered during the

[7] Although the directors and manager were not in the "C-suite" they all oversee reimbursement for organizations of significant size and capacity.
[8] One of the country's largest Medicare billers is included in the sample

interview at least two business days prior to the interview. All potential interviewees were informed that the results of the interviews would be reported in a manner that ensured keeping their identities confidential.

As part of soliciting participants, potential interviewees were informed that they would be asked to have the interview recorded. Additionally, the researcher explained this to the participants prior to conducting each interview. The researcher explained to all interviewees that the recorder was being used to capture quotes accurately and enhance the flow of the conversation. Participants were also told that they could ask the researcher to turn off the recorder at any point during the interview. One interviewee declined to be recorded. During this interview the researcher took extensive hand written notes and wrote direct quotes when possible. All remaining interviews were recorded on an MP3 player and subsequently fully transcribed by the researcher. Eleven participants asked for copies of their transcripts. No concerns were expressed by these participants over the content of the transcripts.[9] Time was spent at the beginning of each interview to establish a rapport with the interviewee and to understand the interviewee's background. The sequence in which issues were addressed varied throughout different interviews. Detailed notes were taken during and after each interview. After each interview, the researcher reflected on the interview and considered possible issues to explore in future interviews.

Data analysis

Consistent with prior research, a three step process was used to analyze the data: data reduction, data display, and conclusion drawing/verification (O'Dwyer 2004; Irvine and Gaffikin

[9] Several participants requested that specific quotes that are in included in the paper be approved prior to inclusion. The quotes were accepted without modification. One of the participants discussed a finding with the researcher that caused the researcher to add footnote 6 to Table 1.

2006; O’Dwyer et al. 2011; O’Dwyer 2011). Data reduction was accomplished by pilot coding the initial interviews (Yin 2009). As the interviews were transcribed and the transcripts were reviewed, the researcher noted that the discussions centered on certain topics. Next, to accomplish data display, a summary was prepared for each of the initial transcripts to easily identify these themes and explain their nature and location within each transcript. As needed, additions were made to these summaries through an iterative process of reading the additional transcripts. Upon completion of the summaries, the researcher proceeded to the conclusion drawing/verification step. A coding scheme was established for the main discussion points of the interviews. The researcher assigned descriptive labels, creating first-order codes, to the main discussion topics while striving to stay as objective and true to the content as possible.

Next, the researcher examined the first-order codes to identify codes to collapse into higher-level nodes, or first-order categories (Glaser and Strauss 1967; Dacin et al. 2010). The categories that emerged were primarily from one section of the protocol (the “ZPIC Audits” section). For example, several participants discussed issues with the time lag for ZPIC auditors to process information. The researcher then identified commonalities among the categories and collapsed them into distinct clusters, or second-order themes (Glaser and Strauss 1967; Dacin et al. 2010). This process identified the following themes: the use of technology and dehumanization of work performed by providers, methods of reporting findings, documentation requests, inadequate communication, the ZPICs perceived inadequate expertise, and societal implications.

Next, the links between these second-order themes were conceptualized as factors that influence and have implications for an overarching dimension. The links identified the central dimension as “ZPIC audit procedures”. For example, auditees expressed concern regarding the

ZPIC audit process highlighting issues such as the ZPICs lack of professionalism, experience and inadequate oversight. The quotes that best represent the main themes identified were selected for inclusion in the findings. Data saturation, a point where additional interviews are neither contradicting nor adding any significant new information (Rahaman et al. 2010; Sutton et al. 2011) was achieved. Additionally, the researcher validated the findings through triangulation of interview data with archival documents (Yin 2009). These documents include communication with the ZPIC auditors from participants and various publicly available information sources such as practitioner websites (i.e.: attorneys, CPAs and consultants). The practitioner literature has largely been consistent with the findings of this study (Vishnevetsky 2012; Van Halem et al. 2012; Moore Stephens Lovelace 2013). While the Reports to Congress portray ZPIC audit activity as being very successful, the reports do not discuss the ZPICs' audit procedures and the implications they have on providers and society—they merely quantify success as based on reported fraudulent funds identified versus cost of audits.

Results

Four requirements of a profession noted above are that professions must 1) develop a unique set of knowledge and expertise and employ this expertise (Kultgen 1988; Covaleski et al. 2003), 2) use this unique knowledge and expertise to make judgments that cannot be preprogrammed or reduced to a set of rules, while allowing the professional discretion to cope with unforeseen problems (Larson 1977; Abbott 1988), 3) hold a credential to certify expertise (Kimball 1995) and 4) support the public interest and not engage in self-interested behavior (Kultgen 1988; Fogarty et al. 2006). The results of this study demonstrate that auditees' observations and perceptions of ZPIC auditors' behavior are inconsistent with the expectations of a profession and as a result, this behavior entails significant concerns for the public interest.

Lack of knowledge / expertise

Importing expertise from a previous domain aids in legitimizing expertise (Latour 1987). Thus, using well-known data analytic developers to assist in developing a data analytical tool helps legitimize this new tool. Consistent with this strategy, CMS used a variety of well-known contractors, including Northrop Grumman, Verizon and IBM to assist in developing a data analytical tool called the Fraud Prevention System (FPS) to help identify Medicare fraud.

Northrop Grumman was selected as the Development Contractor to build, design and implement the data analytics. Northrop Grumman partnered with Verizon's Federal Network Systems to implement their proven predictive analytics technologies into the FPS. Additionally, Northrop Grumman partnered with National Government Services for their Medicare policy and data expertise. IBM had prior experience using predictive analytics in a variety of industries, including health care, and was selected as the modeling contractor to create, refine and test new predictive models. IBM provided CMS with a variety of potential algorithms along with Medicare and Medicaid expertise. The IBM team focuses on developing models and works with CMS and Northrop Grumman to integrate the models into the FPS (DHHS 2012). Using these contractors permitted CMS to leverage preexisting expertise and technology when developing the FPS, and to reinforce its legitimacy. In a Report to Congress, CMS touts the expertise of FPS users and overseers as highlighted by the following:

- Staffed by experts in data analysis, statistics, and behavioral and other social sciences, the Analytics Lab directs the advancements of FPS models, maintaining and refining existing FPS models and guiding the development of new ones (DHHS 2012, pg. 6).

- To provide effective oversight and input to the FPS, CMS assembled an expert, multidisciplinary team in the CPI Analytics Lab. These social science analysts are economists, statisticians, and programmers who research fraud indicators to uncover current and emerging fraud schemes" (DHHS 2012, pg. 14).
- CMS and its contracting partners met or exceeded all SBJA requirements, implementing the FPS ahead of schedule, on a nationwide scale, and with greater capabilities than the SBJA required (DHHS 2012, pg. 4).

Using technology enabled tools, such as the FPS, can be used to control, facilitate and support auditors (Winograd et al. 2000; Banker et al. 2002; Dowling and Leech 2007). In this case, the FPS guides auditor focus and effectively sets risk as very high for conducting substantive tests. Thus, the FPS represents a tool that can be used as a control mechanism to restrict auditors' ability to exercise professional judgment and ensure that predetermined audit procedures are followed when conducting the audit (Dowling and Leech 2014). Centralized expertise, such as the FPS, is designed to facilitate auditors targeting their investigations to the highest risk claims (DHHS 2012; DHHS 2014; DHHS 2015a). While these tools may permit centralized expertise to be disseminated to lower level auditors (Dowling 2009), they may have unintended consequences, such as causing lower level auditors to insufficiently consider issues beyond information identified (Seow 2011). As high risk claims are identified for further audit, it can be argued that there is a decreased need for professional auditors' judgment, with a greater focus on mechanistic tasks in order to achieve positive outcomes. Thus, it may be argued that the ZPIC auditors investigating these high risk claims may not need to be professional level auditors, but rather laborers sufficiently trained to carry out prescribed mechanistic tasks as guided by the data analytics. This is consistent with the ZPIC auditors' charge:

- ZPICs use the FPS to more efficiently and effectively fulfill their responsibility to investigate Medicare fraud in their designated region (DHHS 2012, pg. 15)
- The FPS screens claims data before payment is made, allowing ZPICs to rapidly implement a potential administrative action … (DHHS 2012, pg.15).

This appears contrary to the foundation of professionalism, that prescribes professionals as being required to develop a unique set of knowledge and expertise and to apply that expertise with professional judgment (Kultgen 1988; Covaleski et al. 2003) in situations that cannot be preprogrammed or confined to a set of rules (Larson 1977; Abbott 1988). During the interviews conducted in this study participants frequently expressed concerns with the ZPICs auditors' expertise in conducting healthcare fraud audits. Participants expressed concerns with the ZPIC auditors' domain level expertise, including the acumen behind what the ZPICs were auditing, the lack of judgment utilized in interpreting audit test findings, and the accuracy of the ZPIC auditors' assessments.

Participants expressed concern that the ZPIC auditors were not clear on what they were auditing. For example, the participant employed by arguably the most sophisticated organization in the sample explained that whenever a regulatory agency requests additional charts they are usually able to determine what the auditors are examining, however this was not the case with the ZPIC auditor's request. Although professions are required to hold a unique set of knowledge and expertise (Kultgen 1988; Covaleski et al. 2003), participants expressed skepticism whether ZPIC auditors held such expertise.

- Well, it was really kind of bizarre … the only commonality that we could determine from the sample was that there was some kind of psychiatric diagnosis associated with the inpatient stay… on these particular charts that were pulled … we were grasping to say "I'm not clear what they are looking for" and there doesn't seem to be any big deviation (Participant 4)
- I don't think they know [what they are looking for]. I honestly don't. I talked to several providers and they all agree [with] me, we don't think they even know what they were [looking for] (Participant 2)
- … they got already close to fifty percent of the charts, if they would base it on my current census, or my yearly census in [year], they got, they already achieved at least 50% of that population. That's more than enough, to say, "okay does this agency show any evidence of fraud activity?" (Participant 36)

Participants also highlighted some of the erroneous findings reported by the ZPIC auditors. Three of the participants employed by organizations that are still operating had a final fine that was substantially reduced during the appeals process. Of the overpayments purportedly identified by the ZPIC auditors, the Office of Inspector General (OIG) reports that approximately twenty percent are ultimately collected by CMS (OIG 2017a). This suggests that approximately eighty percent of the improper payments that the ZPIC auditors' report to Congress to justify their cost and report on their performance success are invalidly included. Such reductions are attributable to factors such as the appeals process (OIG 2017a). As expertise is associated with performance (Bédard and Biggs. 1991; Knapp and Knapp 2001; Knechel et al. 2013), such a high error rate suggests low performance, thus low expertise, casting doubt upon the ZPICs' audit expertise.

- …we got a statement from them saying that [fiscal intermediary] should not have re-opened cost reports. That was their mistake. [They're] sorry they did that, but [fiscal intermediary] letters said that they were instructed by … [ZPIC] to re-open all the cost reports and that's what they did, with instruction from [ZPIC]. (Participant 2)
- … the ALJ [Administrative Law Judge][10] found that, that the government really was only due $1,500 some odd dollars, that's a less than 3% error rate [from the initial fine]. (Participant 22)
- I mean this is just extortion … $1.56 million [in fines assessed] turned into $622. (Participant 11)

The results of ZPIC audit activity discussed in Reports to Congress have been portrayed as a success, attributable to an increasing ROI (DHHS 2012; DHHS 2014; DHHS 2015a). Despite the Reports to Congress stating the importance of tracking actual recoveries (DHHS 2015a), the ROIs include funds reported by ZPIC auditors as fraudulent as opposed to actual recollected funds (OIG 2017a). Including only actual benefits reduces the ROI from 3.3:1, 5:1

[10] The Administrative Law Judge (ALJ) represents the third level in the appeals process

and 10:1 for the first three years to approximately 0.5:1, 0.5:1 and 1:1 for the same periods. The OIG highlights the shortcomings in previous congressional reports when examining the ROI calculation:

- ... it is important to track the amounts of actual recoveries that FPS or any of our program integrity activity returns to the Medicare Trust Funds... (DHHS 2015a, pg. 13).
- ... methodology for calculating other reported amounts included some invalid assumptions that may have affected the accuracy of those amounts ... methodology assumes 100% of the amount referred to law enforcement will be recovered (OIG 2012, pg. 5)
- Identified savings does not represent a true return on investment because only a portion of those savings are returned to, or prevented from leaving, the Medicare Trust Funds. (OIG 2014, pg. iii)
- CMS did not use the amounts actually expected to be prevented or recovered (i.e., adjusted savings) to evaluate FPS model performance. (OIG 2017b, pg. 7)

Much of the dissonance in the ZPIC auditors' findings appear to be rooted in an inability to properly integrate FPS data analytic findings with other audit evidence. ZPIC auditors are authorized to extrapolate findings. Several participants reported that the ZPICs would examine the identified sample of high risk medical claims and then extrapolate the audit error findings across the entire population of claims. Yet, the claims identified by the FPS for the ZPICs to audit represent the highest risk claims (DHHS 2014; DHHS 2015a), thus these claims are not representative of the population. As part of the appeals process, participants reported hiring a statistician as a consultant to examine the validity of the extrapolation. The statisticians were able to identify deficiencies in the methods used to extrapolate findings, including that the sample used by the ZPIC auditors to extrapolate was not representative of the population. Thus, the extrapolation methods used represents another area of deficiency in the ZPICs expertise, further highlighted below.

- ... [the statistician] literally tore these people up. As how inept, how ridiculous their formula was, and they couldn't document it, they couldn't back into how they got to this number (Participant 14)

- … threw the extrapolation out because of … data deficiencies, whatever, the way they calculated they couldn't reproduce (Participant 20)
- … the PhD that put that together said … in short, their extrapolations are not reliable (Participant 21)

Taken together, this study demonstrates the lack of knowledge and expertise held by ZPIC auditors. Several well-known contractors were used to develop a powerful data analytic tool (DHHS 2012) in an attempt to use technology, in this case the FPS, to structure the audit process and control auditors (Dowling and Leech 2014). This results in an attempt to bypass the need for auditors to apply unique expertise and professional judgment, which is a requirement of a profession (Kultgen 1988; Covaleski et al. 2003). The evidence calls into question the ZPIC auditors' expertise, and suggest that the nonprofessionalized auditors blindly followed the prescriptions of the automated technology tool without truly understanding how to aggregate and assess the audit evidence.

Make non-programmable decisions

Participants noted the lack of domain specific knowledge required in the findings reported by the ZPIC auditors. Professionalism entails developing a unique skillset and expertise to apply to subjective decision making (Kultgen 1988; Covaleski et al. 2003). Abstract knowledge must be developed by the profession in order to make judgments that cannot be preprogrammed or reduced to a set of rules and allows professionals discretion in coping with unforeseen problems (Larson 1977; Abbott 1988). Several participants discussed that the findings reported by the ZPIC auditors did not require such professional judgment. Medical records may be subject to scrutiny related to the necessity of care delivered, but such scrutiny requires substantial professional judgment and not simply checklist evaluation. Participants were concerned that the ZPIC auditors did not focus on the quality of care delivered to the patient to any extent.

- … what ZPICs are doing, they're just checking off, they're not really reading the medical content of the chart (Participant 12)
- … [ZPICs are] not really looking at what we did for the patient, what's wrong with the patient, how we can took care of the patient, how we had a good quality report (Participant 24)
- ... they're [reimbursement claims] not being denied on [medical] necessity, they're being denied on technicalities (Participant 11)

Overall, the ZPIC auditors' findings were not centered on the quality or sufficient need of care delivered, rather the findings were focused on documentation issues. Focusing on such documentation issues may be reduced to a series of rules, which violates one of the required criteria of a profession (Larson 1977; Abbott 1988). When evaluation criteria are reduced to a set of rules, professional judgment is no longer necessary.

- … we use electronic signatures with a lot of the doctors ... and Medicare accepts it. … when they do it electronically, the little symbol for the electronic signature also prints the date in… And they [ZPICs] denied those claims saying that the doctor did not sign and date the order, he just signed it and the machine dated it. (Participant 9)
- ...they were trying to find any little little spec, not to pay any little claim. (Participant 14)
- ... I will say that they were without question more critical of the charts than any other auditor ... the smallest anything they could find, they found and denied it, they considered the claim no good (Participant 20)

Lack of certification

A requirement of professions is to have extensive training and education (Kultgen 1988) and to hold a credential certifying formal learning (Kimball 1995; Kultgen 1988). Government auditors' qualifications have been questioned by auditees, including auditees claiming to have greater expertise than the auditor (Gendron et al. 2007). Thus, healthcare regulatory auditors, such as the ZPICs, should have a professional background in healthcare and auditing. When professional auditors, CPAs, are faced with performing a task that they do not have the knowledge or expertise to complete, these professionals may bring the desired expertise into the audit team by hiring a specialist. In these circumstances, professional standards (AS 1210) permit auditors to utilize a specialist contingent upon evaluating the specialist's qualification and the auditor understanding the work performed. Although the ZPIC auditors are encouraged to have certain education requirements and certifications (CMS 2007), the results of this study reveal that this does not appear to be the case, and calls into question the ZPIC auditors' professional qualifications. Participants stated that several of their ZPIC auditors were former police officers, which calls into question their health care forensic auditing expertise. There is little evidence of ZPIC audit teams having an adequate level of expertise in audit evidence gathering and evaluation, as well as industry (i.e. healthcare) knowledge. Several participants called into question the ZPIC auditors' professional background and qualifications.

- ... we also ran background checks on the [ZPIC] people. One was a disbarred financial planner, one was a CPA that had his CPA license revoked, and the rest of them were all ex-cops, what the hell do they know about healthcare? … so how can you look at clinical charts and evaluate them if you're not a clinician? ... we're like "what did you make this clinical decision on? you're an ex-cop" (Participant 2)
- … their background was in law enforcement … each one of them went through their background, had nothing to do with healthcare (Participant 24)
- ... none of them are clinicians (Participant 25)

To obtain additional data on the ZPIC auditors' professional backgrounds, a random sample of 180 ZPIC auditors' LinkedIn profiles were examined. The researcher searched LinkedIn using a variety of key words, such as "Zone Program Integrity Contractor", "ZPIC" and the names of the various ZPIC firms. ZPIC auditors come from a variety of professional backgrounds, including law enforcement, healthcare practitioners (e.g. physical therapists), and medical claims analysis. Analysis of LinkedIn profiles suggests that there is a high level of ZPIC auditors with law enforcement backgrounds. While healthcare practitioners may appear to be appropriate auditors, less than 16% of the profiles examined were classified as having a healthcare background.

Proper credentials are required to be recognized as a profession (Kimball 1995). Of the profiles examined, the most prevalent certification was a Certified Fraud Examiner (CFE). Yet, less than fourteen percent of the individuals in this sample claimed to be a CFE.[11] As the CFE certification entails general anti-fraud knowledge (Courtois 2017), ZPIC auditors holding a healthcare specific fraud examination certification, Accredited Health Care Fraud Investigator (AHFI), was examined as well. Of the profiles examined, less than four percent held the AHFI certification. Of the profiles examined, one CPA was identified. Thus, while financial statement auditors are required to have university level education in accounting and auditing plus generally experience working for an audit professional to become a licensed CPA, ZPIC auditors for the most part do not appear to have established comparable professional level certification—a basic expectation for any profession (Kimball 1995; Kultgen 1988).

Public Interest Orientation

While the Reports to Congress suggest significant benefits of ZPIC audit activity, they do not discuss issues of public health and implications for non-fraudulent providers delivery of services after having undergone a ZPIC audit (for example adverse impacts to quality of care or providers refusing to treat patients with certain needs) (DHHS 2012; DHHS 2014; DHHS 2015c). Professions are allowed to exist in order to deliver services that serve society and

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[11] CFE license holders have questioned the rigor of the CFE certification exam and licensure screening process (Courtois 2017)

positively address societal issues and needs (Kultgen 1988; Abbott 1988). Auditees did have a good understanding of the positive effects that could accrue from ZPIC audit activity:

- … I do believe there is a benefit. ... It gets the doctors to take what they do, or how they document what they do seriously. … so that in itself was a huge learning opportunity. (Participant 22)
- … if you were 99.9% compliant before, now you're 99.99% compliant… (Participant 6)
- … ZPICs … regularly engage in education and program integrity activities (DHHS 2014, pg 17)

Yet, not all auditees support the notion of the positive societal impact attributable to ZPIC audit activity:

- … to say there's some education benefit to this … is garbage … it has been an insane distraction for us, that really has zero benefit to the government and zero benefit to the patient. So it's just really a pretty sickening process. (Participant 13)
- … ZPIC [gave] us nothing for denial reasons (Participant 10)

There are several negative implication to society arising from ZPIC auditor activity, suggesting drawbacks of using nonprofessionalized auditors. Several participants expressed intentions to respond to the ZPIC auditors and deter punishment by decreasing the number of Medicare patients treated or to stop treating Medicare patients altogether. This is long standing with healthcare providers changing operations (i.e. patient mix) in response to governmental regulation (Blanchard et al. 1986; Eldenburg and Soderstrom 1996; Eldenburg and Kallapur 1997). If a sufficient number of providers stopped accepting Medicare due to ZPIC audits, it limits the potential provider choices for Medicare consumers. Furthermore, with the expansion of ZPIC auditors' jurisdiction to Medicaid, it could limit the potential provider choices for Medicaid consumers, as well as healthcare providers' ability to sustain operations by diversifying their services. For both Medicare and Medicaid patients, mobility and affordability of traveling greater distances to seek providers is frequently not feasible. Despite the ramifications, the audit outcomes necessitated changes as noted in the following:

- … we’re going to stop taking Medicare totally, because at least we know Medicaid is going to pay. We got to meet our payroll. (Participant 6)
- I had to stop taking Medicare today. I cannot afford to pay staff, phone, lights with no financial relief. (Participant 10 archival document)
- … we are making an assessment if we want to just stay away from Medicare patients all together … this [audit] process bankrupt’s companies. (Participant 16)
- ... providers have voluntarily withdrawn from Medicare after the start of a targeted investigation by our program integrity contractors (DHHS 2015a, pg. 15)

The potential for a company to close down due to a ZPIC regulatory audit is a salient fear, as auditees have been forced to declare bankruptcy due to their ZPIC audit. These effects are driven more by interim effects where the ZPIC auditors can freeze funds from Medicare for an extensive time period pending resolution of purported fraud activity, even though actual collections are ultimately quite low. Bankruptcies limit the number of providers availabe to deliver Medicare services to those in need and presents issues for access to care for Medicare beneficiares. The potential for auditees to simply close their doors after a ZPIC audit appears very real.

- … small mom and pop that are just a one location thing, if they ever faced this they’d be out of business… (Participant 13)
- … we’ve heard that there’s companies that completely shut down. And then when they go to appeal the judge rules in their favor, but there’s no company any more (Participant 16)
- … I bought one of my nursing homes because they had gotten hit and couldn’t survive this. (Participant 2)
- The ZPIC eventually caused us to sell… (Participant 21)

Examining the quality of care delivered by healthcare providers is largely overlooked by accountants (Pflueger 2016). Hindered patient care adversely impacts patient satisfaction and ultimately decreases the likelihood of a patient seeking medical aid when needed, complying with a therapeutic regimen and maintaining a relationship with a physician (Larsen and Rootman 1976). Thus, not surprisingly, overseers of ZPIC auditors emphasize their commitment to ensuring that operational disruption is minimal and quality of care is not adversely impacted.

- CMS is committed to ensuring that fraud prevention efforts do not place unnecessary administrative and compliance burdens on legitimate providers nor interfere with their business operations (DHHS, 2012, pg 34)
- The FPS governance process ensures that the system's ... sophisticated analytics minimize impact on beneficiaries and legitimate providers and do not adversely affect the quality of health care. ... Reducing fraud contributes to ensuring that beneficiaries have access to quality health care. ... when fraud occurs, there are direct human costs (DHHS, 2012, pg 33).

Yet, several participants reported disrupted operations and/or hindered quality of care during their ZPIC audit. One of the providers in the sample is the only provider in the region that provides services over the weekend, thus without this provider, patients would have to wait for services or simply not have services when needed, harming the public good. Another participant described that despite being the largest provider in the country for a specific type of service, part of their ZPIC audit settlement stated they were prohibited from continuing to provide that service. This is particulary troubling given that "patient experience / satisfaction" is a top priority of healthcare providers (The Beryl Institute 2015).

- … I think the most challenging process was the allocation of resources and time spent from our team that took us away from patient care. Because most of our really, really good clinical nurse leaders needed to be putting these charts together [for the auditor] (Participant 3)
- … do I think care was compromised? I most certainly do (Participant 34)
- … the patients are the ones who are suffering. Absolutely the patients are the one's who are suffering (Participant 25)

Taken together, a picture comes together that suggests it is not uncommon for providers subject to ZPIC audits to be at risk of declaring bankruptcy. Of the agencies in this study that have been able to avoid declaring bankruptcy, several have expressed intentions to stop delivering Medicare services. These two factors limit the number of providers operating that will deliver Medicare services. Finally, of the agencies in this study that did continue delivering Medicare services, several reported a decline in the qualty of care delivered. Thus, among the more limited set of providers available to deliver Medicare services, the quality of care was lowered as a result of the ZPIC audits.

Choosing proper indicators to evaluate the performance of government auditors is essential (Gendron et al. 2007), and the results of this study demonstrate that merely focusing on the ROI of ZPIC audit activity does not provide a comprehensive understanding of their actions. Further, the ROI that is used is based on flawed data. As professions are required to serve the public (Kultgen 1988; Abbott 1988), the nature of the ZPIC audit process that elects not to engage audit professionals is a failure to promote the very public interest that the audit process is designed to provide. These results suggest additional consideration of the benefit of using audit professionals to perform audits should be given with the inherent codes of conduct that reject self-interested behavior adversely impacting society.

Discussion

While examining the use of nonprofessionalized auditors in a critical audit setting, several differences from the results presented in the Reports to Congress were identified. Throughout the interviews, participants discussed other healthcare regulatory auditors, and at times making comparisons of these other auditors to the ZPIC auditors. The insights taken from these interviews suggests that the findings noted above are not simply the result of having an audit, but confined to the nature of the ZPIC audit process. Participants' discussion of other regulatory auditors highlights the distinctions from the ZPIC auditors:

- …The government is more willing to help and work with you if it's not intentional fraud or abuse. With the ZPICs it's more of 'this is what you're paying us, have a good day' (Participant 3)

- … [ZPIC] main objective was to close down agencies… most auditors that I've been through, their main objective is to come in and educate. … If you feel we need to be educated fine educate us, but that's not enough reason to shut an agency down. (Participant 25)
- …[other auditors] do an entrance conference with us to kind of meet with the people that they should meet with, establish the parameters of the survey ... most surveys we sort of get, sort of an informal daily assessment "hey guys we found this, we saw this, we liked this, we're still looking for this" … they always do an exit interview at the end of the survey where they say "here's a list of our preliminary findings" and at that point we have an opportunity to say you know "I'm confused about this" or "didn't you see this piece of paper" ... little minor issues are headed off at that point. … 9 out of 10 times of what they said at the exit is what we actually see on the survey report. Once in a blue moon they put something a little different of a twist in there ... There is a lot of feedback along the way … [with ZPICs] It's just a letter and then you submit your records, and then it's another letter saying you're a criminal and you owe a gazillion dollars (Participant 13)
- … what's ironic is every single one of my agencies went through a survey, accreditation survey ... And I went through a [audit] survey, and it went fine. And I went through an [audit] survey, and I went through a state audit surveyor from [audit], so cause each branch had a different requirement for survey, and I went through all 3 of them, no problems (Participant 28)

Participants also discussed their interactions with their CPA firm that provides the annual financial statement audit:

- … [financial statement auditors] they're good to deal with, and the banks we deal with seem happy with the financials that are produced. (Participant 20)
- …[financial statement auditors] they're very client oriented. They come in they consult with me, tell me what they think, tell me where I can improve it … from an accounting standpoint we're sparkling clean because we take care of suggestions and improve our operations. They do an outstanding job. (Participant 21)

Participants also discussed their perceptions of the fraudsters that the ZPIC auditors were able to identify. Overall, the participants were supportive of fraudsters being identified and even shut down. This suggests that participants are supportive of the government's initiatives to identify fraud.

- The ones that are blatantly across the board committing fraud, shut them down, I have no problem with that… (Participant 25)
- But if they [ZPIC] are there and you [provider] did commit fraud I'm happy as heck (Participant 11)
- … [convicted fraudsters] needed to be handled appropriately and should've been shut down (Participant 32)

Several factors may be contributing to the gap between how the Reports to Congress discuss the ZPIC auditor's performance and the results presented above. These factors may help ensure that such a gap does not manifest in the public accounting profession as it becomes increasingly de-professionalized (Dirsmith et al. 2015). Contributing factors may be the power provided to the ZPICs, their incentive structure and the manner in which advanced technologies are used.

Power

Actors in power can influence those with less power (Kipnis 1972). Such power may be used to repress, censor or constrain those subject to this power (Foucault 1983). Holding such power via resource dependence enables powerful actors to exert unethical demands on less powerful actors (Palmer 2012; Marmor and Morone 2005). The ZPIC auditors exhibit substantial resource dependence over auditees, as ZPIC auditors hold the power to suspend Medicare cash flow (DHHS 2012). For example, if a provider derives fifty percent of their revenue from Medicare, the ZPIC auditors have the ability to temporarily eliminate half of the provider's cash flow. Thus, ZPIC auditors are in a position of power over auditees. This is substantially different from a financial statement auditing setting, as financial statement auditors hold minimal, if any, power via resource dependence over auditees. Participants discussed the ZPIC auditors' use of this power, including exercising this power without communicating with the auditee in a timely manner.

- … we received a letter May 12th stating that we were on Medicare suspension effective May 6th. … on CMS letterhead from [ZPIC] signed by [ZPIC employee]. And that prior notice of suspension was not provided because the [Medicare] trust funds would be harmed (Participant 25)

- … letter said that we would be under suspension effective that day (Participant 33)
- … even though [fiscal intermediary] controls the money, they respond to ZPIC. When ZPIC says put a hold on this, they just put a hold on it mindlessly. (Participant 36)

While CPAs are held accountable by the PCAOB (PCAOB 2007; PCAOB 2008), such oversight is not apparent for the ZPIC auditors. While CMS has the responsibility to oversee the ZPIC auditors (CMS 2007), CMS appears to provide limited oversight over the ZPIC auditors (DHHS 2011; Van Halem et al. 2012).[12] While inadequate oversight may result in ineffective audit services being provided (Okma et al. 2011), limited oversight may also create an opportunity for some ZPICs to exhibit behaviors perceived as unprofessional.

- There's a lot power at the ZPIC level right now, and that needs to be balanced … It is very discouraging to downright criminal the abuse of power that we are currently seeing from the ZPICs and other entities that are letting this happen such as CMS/[D]HHS (Participant 29)
- Because they know that they are really putting us in a situation, and they have that power. ... You give power to somebody … they know that they have the power to close you down and take everything away (Participant 30)
- … Essentially, ZPICs consider themselves above the law. Efforts to persuade them to moderate or reverse course on any aspect have fallen on deaf ears. … The letter [ZPIC] sent was from a manager, and not copied to or to our knowledge reviewed by any lawyer. The admissions of extra statutory conduct and claims of immunity from statutory, regulatory, and even policy manual protections is amazing. (attorney from archival documents)

Additionally, some participants highlighted that despite not being physicians, and having a lower level of education than physicians, ZPICs have the power to override a physician's judgments.

- … They can override a physician's face to face that CMS put in place. They can override a clinician's determination (Participant 25)
- …this is a nurse who's questioning a physician's orders (Participant 10)

[12] Upon review of archival documents an attorney stated: "…the conduct of ZPICs here and elsewhere in this country is outrageous. CMS' failure to police the ZPICs and confine them to justifiable fraud investigation is also unacceptable…"

Taken together, this section demonstrates how ZPIC auditors are placed in a position of power over auditees (DHHS 2012). This power becomes uninhibited with the lack of oversight from government agencies (DHHS 2011), enabling behavior perceived as lacking professionalism. The results suggest that ZPIC auditors willfully exercise their power by imposing cash flow suspensions on auditees and by overriding the professional judgments of individuals with high levels of domain knowledge.

Incentive structure

ZPIC firms compensation switched fairly recently from primarily cost reimbursement (DHHS 2012; DHHS 2014) to the amount of fraudulent dollars reported (DHHS 2015c). Yet, a Freedom of Information Act (FOIA) request of the ZPIC firms' compensation contracts revealed that ZPIC firms draw over 90% of their compensation from cost reimbursement, and that no change in compensation structure occurred. Thus, ZPIC auditors are financially incentivized to follow even frivolous leads which incur greater costs and increase the firm's compensation. ZPIC firms' also have incentive to utilize audit procedures and interpretations of findings that make them appear more successful, as their responsibilities are being consolidated by CMS with their Medicaid counterparts to create Unified Program Integrity Contractors (UPICs). By increasing their reported results, ZPIC firms can increase the likelihood of expanding their jurisdiction and increasing future revenue through additional contract awards. As engaging in self-interested behavior is prohibited for professionals, this type of conflict of interests is the primary reason professional auditors are not allowed to charge contingent fees. This financial incentive appears real as all but one of the ZPIC firms were awarded a UPIC contract. Evidence of anticipated expansion can be seen from participants receiving requests to submit Medicaid documentation for requests.

- … they said "we need 40 charts, only this time we need your Medicare and we need 40 more on your Medicaid side"… on the Medicaid side, I said "I didn't know you were allowed to-" "it's a pilot program, and this is the way we're doing things now" (Participant 11)
- … [attorney] stated that they didn't have authority to request the Medicaid records (Participant 16)

These results demonstrate how the cost reimbursement compensation structure provides an incentive for ZPIC auditors to perform inefficient work and to impose additional work on auditees. This method of creating an appearance of competence and thoroughness appears to be effective given the first UPIC jurisdiction contract was awarded to a former ZPIC auditor. Additionally, although only one UPIC jurisdiction has been awarded to date, two former ZPIC audit firms were awarded ad hoc contracts.

Use of advanced technologies (FPS)

Using advanced technologies, such as data analytics, can enable auditors to reduce time spent on labor intensive tasks and reallocate this time to judgment intensive tasks (Brown-Liburd et al. 2015; Agnew 2016b; Raphael 2017). Although data analytics are more effective at identifying statistical outliers, these outliers may merely represent false positives (Vasarhelyi et al. 2015; Yoon et al. 2015), that have legitimate explanations (Kogan et al. 2014). As the potential usefulness of data analytics are limited by the capabilities of the human users (Alles and Gray 2015), training auditors to effectively use data analytics is essential. When decision makers use data analytic tools to aid in their decision making, relying on the analytics without understanding the process used by the analytic results in a missed opportunity for the decision maker to learn from their mistakes (Mayer-Schonberger and Cukier 2013). Thus, there is a missed opportunity for the decision maker to enhance their expertise and results in hindering their professional development. Subsequent to the FPS identifying an outlier, ZPIC auditors may feel pressure to report an error associated with the identified outlier, as the outlier by definition represents a high-risk account or transaction. This is concerning given the level of specialization in the healthcare industry (Mashaw and Marmor 1994; Cassel and Reuben 2011), which by the nature of specialization yields outliers that will not appear typical but are clearly explainable. Concerns expressed by participants regarding the use of the FPS provide insights to this problem:

- … just to be presumed guilty by a statistical analytic, has never been done before. … they said anybody in our sample … because they were statistical outliers, we're assuming you did something wrong and therefore we're not paying you. … every bill that was pulled was denied 100 cents on the dollar, denied, because statistically it didn't make sense to somebody. … There's no concept of an average family because the average family has one and three quarter kids, so it doesn't exist. Statistically you can have an outlier, but that doesn't mean you did anything wrong … (Participant 6)
- … [the physician] came up on somebody's radar and because he's a specialist, he's geriatric, so 70% of his patients are all going to be in the Medicare aged… (Participant 29)

Despite the potential benefit for data analytics to identify high risk audit areas, these results highlight challenges to implementing data analytics into a highly specialized industry, specifically healthcare. The ZPIC auditors may feel compelled to report findings identified by the analytics, as the highest risk areas have purportedly been identified. Thus, the FPS may provide justification for the ZPIC auditors' behavior.

Conclusion

Increased competition in the audit market has resulted in increased pressure for firms to reduce audit fees (Dirsmith et al. 2015). This fee pressures has led to the commodification of audit services. Technology enabled tools promise to further enable the commodification of services, as these tools enhance firms ability to disseminate centralized knowledge and control auditors' ability to exercise professional judgment (Dowling and Leech 2014). To the degree the audit process can be defined by a series of mechanistic procedures, the greater the potential for audit professionals to be replaced with lesser trained nonprofessionals. Commodifying professional services results in commercialization of a profession—a transformation from a profession to an industry.

Two distinct camps discuss the use of commercialization tactics by professions. While one camp views professions engaging in commercialization tactics as shifting from an economically disinterested expert to an entrepreneur (Abbott 1988; Reed 1996), the other camp views professions engaging in commercialization tactics as seeking to deliver additional needed services to society (Dirsmith et al. 2015).

This study reports the results of constructing nonprofessionalized auditors to examine the use of nonprofessionalized auditors in a critical audit context. Results from this study illustrate issues of using nonprofessionalized auditors in a critical audit setting, and how these auditors' practices adversely impact society. Despite the ZPIC auditors' creation to fight fraud, of the fines participants in this study incurred, none were fraud related. All fines reported in this study were related to alleged insufficient documentation. The demands the ZPIC auditors placed on providers has in many cases resulted in patient care suffering, which in extreme cases may lead to death. While accounting devices such as the FPS may be used to remake and define the patient in accounting terms in an attempt to reduce waste (Kurunmäki 1999; Llewellyn 1998; Preston 1992; Samuel et al. 2005; Covaleski et al. 1993), such devices can blur the line between cost and caring (Llewellyn 1998; Samuel et al. 2005).

The results of this study are particularly concerning, as the public accounting profession has been exhibiting a trend toward declining professionalism (Dirsmith et al. 2015). If the public accounting profession continues de-professionalizing, potentially even to the point that society no longer sees the need for the profession to retain its monopolistic rights over financial statement auditing, similar results to those seen in this study that are associated with using nonprofessionalized auditors may manifest in the public accounting profession. Research has already noted the lack of focus by public accountants on serving the public interest (Cooper and Robson 2006). Although the public accounting profession seeks to expand its services (Gendron and Barrett 2004; O'Dwyer 2011; Suddaby et al. 2009), it is imperative that public accounting seeks to rebuild and regain its professional stature.

Despite the attempted transparency of ZPIC audit activity through Reports to Congress, these reports focus on financial numbers and do not discuss the real societal implications of ZPIC audit activity (i.e., patient care suffering and providers refusing Medicare patients). This is consistent with actor's manipulating information in order to achieve certain ends (Nizet and Rigaux 2014; Goffman 1959), such as using language to manage public impressions to aid in legitimization (Suddaby and Greenwood 2005; Hopwood 2009), and governments focusing on outputs and not expertise (Gendron et al. 2007). Additionally, the Reports to Congress seem to present improper payments identified by the ZPICs, not improper payments recollected by CMS (DHHS 2015b; OIG 2017a). Over one third of appeals are ruled entirely in the provider's favor (DHHS 2015c), and evidence from the sample indicates that partially favorable decisions through appeal result in substantially reduced fines. Thus, it is vital for effective oversight to consider a range of metrics to evaluate the success of nonprofessionalized auditors, such as the ZPICs. It is for this reason that professions are often allowed to exist and self-regulate—it is difficult for those that are not a part of the profession to assess the level of performance in such services.

Like any research study, this paper is subject to limitations. The first limitation is attributable to the sample size. While a limited number of individuals were interviewed it is possible that other ZPIC auditees would have constructed their ZPIC auditors more positively, however the results of the study are consistent with the practitioner literature of issues identified with ZPIC audits. Similarly, the sample does not extend to providers that were actually found guilty of fraud. While human subjects research approval was obtained to interview prisoners, to date the researcher has been unable to reach any volunteers in this population willing to be interviewed. Further, participants from all seven zones did not participate in this study, and all four ZPIC firms were not included in the sample. While it is possible that different individuals would have constructed their audit experience differently from the other ZPIC firm not included in the study, there is no compelling reason to believe that this would be the case, and no substantial distinctions between ZPIC firms are noted in the practitioner literature. Finally, the study began with a convenience sample, then additional participants were pursued in potentially underrepresented groups to enhance validity and reliability.

The results of this study present a glimpse at examining nonprofessionalized auditors in a critical audit setting. Future research may seek to examine how other nonprofessionalized auditors act in a professional setting. Throughout the data collection process, some individuals speculated that the ZPIC auditors are focusing a disproportionate amount of resources on smaller/minority providers, which would be consistent with prior research's discussion of political markets targeting those with disproportionately lower resources (Marmor and Morone 2005). This is an example of previous research discussing how technology may be misused to target certain groups or individuals (Newell and Marabelli 2015) such as the indigenous, low-income and women (Everett et al. 2007). While larger providers have successfully resisted activity of healthcare regulatory auditors (as demonstrated by *American Hospital Association vs. Kathleen Sebelius*[13]*)*, small organizations may be unable to make their story visible (Roberts 2015), allowing a phenomena, in this case the ZPIC audit tactics, to go undetected by society (Neu et al. 2015) and remain a secret (Shleifer and Vishny 1993). Future research may seek to examine if nonprofessionalized auditors are more likely than professional auditors to focus a disproportionate amount of resources on risks related to smaller/minority agents. The Reports to Congress describing the ZPIC activity have cited the "Sentinel Effect" as an added benefit of ZPIC audit activity, suggesting that providers will be less inclined to engage in fraudulent activity subsequent to hearing about the ZPIC auditors' capabilities. Yet, empirical evidence of the Sentinel Effect in a fraud setting does not appear to exist. Future research may seek to examine the impact the examples of audit procedures and tactics noted in the paper are having on providers not yet subjected to a ZPIC audit and their viability in reducing fraud risk, an area gaining increasing attention in the literature (Power 2013).

[13] This lawsuit focused on the location of patient care (inpatient vs outpatient) for billing purposes. Recovery Audit Contractors were denying reimbursement of inpatient claims, stating the services should have been provided outpatient. By the time the denial was made, hospitals were beyond the timeframe to bill for outpatient services, thus received no revenue for services provided. The ruling stated that if an inpatient claim was rejected, an extension would be granted to resubmit the claim for outpatient reimbursement.

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STUDY TWO: THE IMPACT OF DATA ANALYTICS ON AUDITORS' JUDGMENTS AND DECISIONS

Introduction

Recent advances in technology have caused auditors and firms to increase their use of data analytics (Deloitte 2010; AICPA 2015a; Coffey 2015; Ernst and Young 2015a). Advances in technology have facilitated development of more sophisticated data analytical tools and hold great promise for implementation into the audit process. These new analytical tools extend audit capabilities by enabling testing of entire populations to identify all outliers based on established criteria (Jans et al. 2014; Kogan et al. 2014; Sinclair 2015; Raphael 2017; Agnew 2016b; Titera 2013; Alles 2014; Gray and Debreceny 2014; Richins et al. 2017; Huerta and Jensen 2017; Jans et al. 2010). Additionally, data analytics can be used for predictive modeling (Kuenkaikaew and Vasarhelyi 2013; Statistical Analysis System (SAS) Institute 2014; Krahel and Titera 2015), cluster analysis (Thiprungsri and Vasarhelyi 2011) and unstructured data analysis such as text and videos (Holton 2009; Vasarhelyi et al. 2015; Yoon et al. 2015; Warren et al. 2015; PCAOB 2016; Agnew 2016; IAASB 2017; Raphael 2017). Data analytics hold the potential to fundamentally change the audit process by greatly reducing the distinction between analytical procedures and substantive testing (Jans et al. 2014; Kogan et al. 2014). Furthermore, data analytics may help minimize the risk of failing to identify an existing misstatement, resulting in improved audit quality and effectiveness, and greater value for audit stakeholders (Agnew 2016b; Raphael 2017; Titera 2013).

While data analytics hold the potential to fundamentally change the audit process, prior research examining the impact of data analytics on auditors' decisions is limited. Rose et al.

(2017) examines the impact of the timing of data analytics visualizations and processing mode has on auditors incorporating data analytics into their judgments. The results demonstrate that auditors are not effective at identifying patterns in data analytics visualizations when viewed before traditional audit evidence (Rose et al. 2017). Further, the question of whether auditors will incorporate the information generated from the data analytics into their decision process is unknown. Prior research examining other decision aiding tools indicate that auditors do not always incorporate the information into their decisions (Sutton et al. 1995). This may be attributable to auditors reluctance to investigate identified risks, as auditors face criticism from supervisors when no error is identified subsequent to investigating such risks (Brazel et al. 2016). Thus, while data analytics may be very effective at identifying audit relevant information that can improve the audit process, the use of data analytics may be constrained by the decision maker (Alles and Gray 2015). The mere availability of these tools is insufficient to improve decision maker performance, as no improvement in performance will be observed if these tools are not used (Davis et al. 1989; Venkatesh et al. 2003). While incorporating data analytics into the audit process has several practical implications, such as reducing labor intensive tasks and allowing auditors to focus more on judgment intensive tasks (AICPA 2015a; Brown-Liburd et al. 2015; Agnew 2016; Raphael 2017), if auditors refuse to use data analytics these benefits will not be realized.

The incorporation of these new data analytical tools into the audit process is highlighted by a joint initiative between the AICPA and CPA Canada encouraging increased use of data analytics in the audit process (Coffey 2015) as well as the development of data analytical standards by the AICPA's Assurance Services Executive Committee (ASEC) (AICPA 2015b; Appelbaum et al. 2017; AICPA 2017). The IAASB has also expressed interest in increasing the use of data analytics in the audit process to in an effort to enhance audit quality (IAASB 2017). This demonstrates that data analytics will play a more pronounced role during the audit process; thus, examining the impact of various inputs, such as the type of data analytical model and type of data analyzed, on auditors' decisions is essential. If auditors do not adequately understand the analysis performed by the data analytics and properly utilize these analytics, the result is a potential missed opportunity to improve the audit process and audit quality (PCAOB 2016). The purpose of this study is to examine whether auditors' decisions are impacted by the type of data analytical models used and the type of data analyzed by the models.

A 2 X 2 experimental design is used to examine the impact of the type of data analytical model (predictive vs. anomaly) and type of data analyzed (financial vs. nonfinancial) on the decisions of 98 auditors. Anomaly models identify unusual activities by performing a distributional (bell curve) analysis to identify outliers that may warrant additional scrutiny (SAS 2014). Predictive models use forward-looking analytics that analyze patterns of previously identified issues and compare them to current patterns, creating the potential to identify issues before they occur (Kuenkaikaew and Vasarhelyi 2013). Although prior archival research demonstrates that predictive models can help identify heightened fraud risk (Perols et al. 2017; Dechow et al. 2011), it is unclear if auditors use these models. Further, these data analytical models are capable of analyzing unstructured nonfinancial data, which creates new opportunities for auditors to identify audit relevant information from sources such as e-mails, phone calls and board minutes (Warren et al. 2015; Vasarhelyi et al. 2015; Agnew 2016; PCAOB 2016).

Using cognitive fit theory, auditors are predicted to have greater cognitive fit with data analytics generated using anomaly models. Cognitive fit occurs when there is congruence between the method or process used by a decision maker and a decision facilitating tool (Vessey and Galletta 1991; Arnold and Sutton 1998; Al-Natour et al. 2008). Auditors are experienced in using analytical procedures, which are similar, albeit simpler, versions of anomaly models (Hirst and Koonce 1996; Cohen et al. 2000; Asare et al. 2000; Glover et al. 2005; Brazel et al. 2009; Brewster 2011; Brazel et al. 2014) and are more familiar with using anomaly models. Predictive models have been noted as more accurate and reliable than other analytical models and are most suitable for complex patterns as they can identify otherwise undetectable and seemingly unrelated patterns (SAS 2014; DHHS 2015). Unfortunately, auditors are largely unfamiliar with the methods used by predictive models, thus these models will likely have lower cognitive fit with an auditor's decision making process. Auditors are not as effective at analyzing nonfinancial data as compared to financial data (Cohen et al. 2000; Brazel et al. 2009; Brazel et al. 2014). Thus, auditors' judgments are expected to be more impacted by the results of data analytics using financial data due to high cognitive fit.

The results of the study indicate that neither the type of data analytical model nor the type of data analyzed affects auditors' fraud risk assessment or reliance. Interestingly, the two variables have an interactive impact on budgeted hours. Specifically, when financial data is analyzed, auditors increase budgeted audit hours more when this data is analyzed by predictive models compared to anomaly models. The opposite is true when nonfinancial data is analyzed, as auditors increased budgeted audit hours more when this data is analyzed by anomaly models compared to predictive models.

The results of this study have implications for practice and research alike. The implications of this study are timely and important given the interest to increase the use of data analytics throughout the audit process from the AICPA and CPA Canada (Coffey 2015), the IAASB (IAASB 2017) and the AICPA's development of data analytical standards (AICPA

2015b; Appelbaum et al. 2017; AICPA 2017). Furthermore, public accounting firms and government agencies have demonstrated a commitment to incorporating data analytics into their respective audits (DHHS 2015; Ernst and Young 2015b; Wall Street Journal MoneyBeat 2015). The results of this study suggest that while data analytics impact decisions uniformly for certain tasks (i.e., fraud risk assessments), decisions for other tasks (i.e., determining budgeted audit hours) are jointly impacted by the type of data analytics used and the type of data analyzed. This study contributes to the literature on the impact data analytics have on auditors' decisions. Research on data analytics impacting auditors' decisions is limited to demonstrating that the timing of viewing the results of analytics impacts auditors' judgments (Rose et al. 2017). This is the first study to show that the new types of data analytics and data analyzed have a joint impact on auditors' judgments. Additionally, this study provides initial evidence that different types of data analytics impact budgeted audit hours decisions.

The remainder of this paper is comprised of four sections. The following section discusses insights from the academic literature into the use of data analytics and auditors' judgment and decision making. Section three discusses the research methods. The fourth section discusses the results of this study. The final section presents a discussion of the findings and concluding remarks.

Background

Data Analytics

As technology advances, the capability of and interest in analytics, including the analysis of unprecedentedly large data sets, in the accounting literature has expanded (Alles and Gray 2015). In line with the expansion of capabilities of analytics, the AICPA's Assurance Services

Committee (ASEC) is developing an "Audit Data Analytics Guide" to replace the Analytical Procedures Guide, suggesting that these new data analytics are an outgrowth and expansion of analytical procedures (AICPA 2015b; Appelbaum et al. 2017). Thus, analytical procedures can be viewed as a predecessor and subset of data analytics. Data analytics entail a greater ability to disaggregate and perform analyses than analytical procedures (Titera 2013), holding the potential to perform more sophisticated analyses and obtain better insights from data (PWC 2015). Audit data analytics are defined 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). The Data Analytics Guide identifies various uses for data analytics during the audit process, including risk assessment, testing controls, and substantive testing (AICPA 2017). Similar to the AICPA's ASEC committee, the IAASB has established the Data Analytics Working Group (DAWG) (IAASB 2017). The primary objectives of the IAASB's DAWG is to determine how to effectively use data analytics in the audit process to enhance audit quality and to consider revising international standards to allow for data analytics to be used in the audit process (IAASB 2017). Furthermore, Chief Audit Executives of Fortune 500 corporations revealed that data analytics are drastically changing their organization's internal audit processes (Rose et al. 2017).

The expansion of database sizes and analysis capabilities provides new opportunities on how to utilize data analytics (Warren et al. 2015). Improving analytical abilities over datasets may be utilized to identify new audit relevant information (Jans et al. 2014; Kogan et al. 2014; Jans et al. 2010), and improve fraud prevention and detection initiatives (Brivot and Gendron 2011; Jans et al. 2014; Smith 2016; Titera 2013; Jans et al. 2010). New methods of analysis including pattern recognition, data mining, and language processing are now available (Yoon et al. 2015). Several papers in a recent *Accounting Horizons* special issue on data analytics discuss the use of nonfinancial measures (e.g., Yoon et al. 2015; Vasarhelyi et al. 2015; Warren et al. 2015). Additionally, new data such as video surveillance, news videos, cell phone videos (Vasarhelyi et al. 2015), e-mails and social media postings (Warren et al. 2015) can now be analyzed. Auditors must implement new audit techniques enabled by these tools to keep pace with the changing business environment (Rezaee et al. 2002).

Incorporating data analytics into the audit process has several practical implications, such as reducing labor intensive tasks and allowing auditors to focus more on judgment intensive tasks (Brown-Liburd et al. 2015; Agnew 2016b; Raphael 2017). This will facilitate faster and more comprehensive auditing (Raphael 2017). The ability to analyze entire populations in conjunction with expanding visualization capabilities has the potential to enhance audit quality and create more value for audit stakeholders (Sinclair 2015; Agnew 2016b; Raphael 2017). Yet, incorporating these data analytics into the audit process will likely require expanding the analysis capabilities of audit teams (Richins et al. 2017). An example of how data analytics can identify audit relevant information can be seen from process mining, the examination of chronological records of computer system activities (Jans et al. 2014; Jans et al. 2010). Jans et al. (2014) conducted process mining of event logs of procurement data to identify transactions containing audit-relevant information such as payments made without approval. The results demonstrate that data analytics can be used to identify financial accounting exceptions, breakdowns in internal control and even possible fraud using nonfinancial data. This study also demonstrates how social network analysis may be used to facilitate identification of collusion.

Auditors use technology enabled tools, such as computer-assisted audit techniques (CAATs) (Janvrin et al. 2009). Thus, auditors are expected to use other technology enabled tools, such as data analytics. Auditors typically use CAATs to facilitate their understanding of the client systems and business processes, to test computer controls and to evaluate fraud risks (Janvrin et al. 2009). While it is less common for auditors to use CAATs for substantive testing (Janvrin et al. 2009), data analytics provide an opportunity to facilitate substantive testing (Jans et al. 2014; Kogan et al. 2014). Auditors are more likely to use computer-related audit procedures and IT specialists when control risk is set as less than maximum, suggesting that such technology enabled tools are more commonly used for lower risk functions (Janvrin et al. 2009). As larger firms tend to have more CAAT resources readily available to their staff (Banker et al. 2002; O'Donnell and Schultz 2003), auditors at larger firms are more likely than smaller firms to use CAATs (Janvrin et al. 2009). Auditors are more likely to use CAATS when they have greater expectations of the CAATs, greater organizational pressure to use CAATs and greater technical support infrastructure to implement CAATs (Bierstaker et al. 2014). The mere availability of these tools is insufficient to improve decision maker performance, as no improvement in decision maker performance will be observed if such tools are not used by the decision maker (Davis et al. 1989; Venkatesh et al. 2003).

Prior research on data analytics has focused on developing data analytics for more effective outlier identification (Jans et al. 2014; Kogan et al. 2014), however there is a lack of research examining auditors' use of data analytics (Brown-Liburd et al. 2015). As previously stated, data analytics can be viewed as an outgrowth of analytical procedures. While the focus of this study is on auditors' decisions using data analytics, an area receiving limited attention from the prior literature, additional insights on this topic can be obtained from examining auditors' use of analytical procedures (see Messier et al. 2013 for a review). Analytical procedures are often used by auditors during planning, and have been shown to influence auditors' nature, timing and extent of substantive testing (Asare et al. 2000). Analytical procedures aid auditors, particularly more experienced auditors, in making more effective fraud risk assessments (Knapp and Knapp 2001). The results of analytical procedures impact auditors' judgments more when auditing high risk clients (O'Donnell and Schultz 2005). Auditors perceive analytical procedures as stronger when they present a lower risk of misstatement (Glover et al. 2005). Additionally, altering the presentation of the results of analytical procedures has been shown to lead to more effective decisions (O'Donnell and Schultz 2003; Knechel et al. 2010; Brewster 2011).

PCAOB inspections have identified several deficiencies in auditors' use of analytical procedures (PCAOB 2007a; PCAOB 2007b; PCAOB 2008). This suggests that auditors may not be using analytical procedures properly (Messier et al. 2013). As data analytics may be viewed out an outgrowth of analytical procedures, such improper use may continue for auditors' use of data analytics. Deficiencies identified by the PCAOB relating to auditors' use of analytical procedures include auditors insufficiently investigating unexpected fluctuations identified by analytical procedures (PCAOB 2008).

Although prior research has focused on auditors' use of analytical procedures using financial measures (Asare et al. 2000; Knapp and Knapp 2001; O'Donnell and Schultz 2005), research has also examined the incorporation of nonfinancial measures in analytical procedures (Cohen et al. 2000; Brazel et al. 2009; Trompeter and Wright 2010; Brazel et al. 2014). Nonfinancial measures can be used to develop more precise expectations for analytical procedures (Trompeter and Wright 2010). Examples of nonfinancial measures that can be used in analytical procedures include employee headcount, production space, warehouse space, trading volume, retail space, economic conditions, industry changes, growth, and market penetration (Amir and Lev 1996; Cohen et al. 2000; Brazel et al. 2009; Brazel et al. 2014). Industry specific examples of nonfinancial measures may be valuable as well; for example, in the healthcare industry, the change in the number of provider locations can be considered in conjunction with the change in assets and/or revenue (Brazel et al. 2009). Nonfinancial measures are often less complex to determine than financial measures and verification is often more straightforward (e.g. number of employees vs. oil and gas reserve) (Brazel et al. 2009).

Despite the benefits of nonfinancial measures, auditors experience difficultly incorporating nonfinancial measures into their analytical procedures as compared to financial measures (Cohen et al. 2000; Trompeter and Wright 2010). Rather, auditors focus more on analytics using financial data (Cohen et al. 2000; Brazel et al. 2014) and only respond to inconsistent results presented from financial and nonfinancial measures when prompted to do so (Brazel et al. 2014). As inconsistencies among financial and nonfinancial measures are greater among firms where fraud has occurred, analytical procedures using nonfinancial measures have the ability to enhance fraud identification (Brazel et al. 2009). This may be attributable to nonfinancial measures not being the focus of manipulation by management while engaging in fraudulent financial reporting (Cullinan and Sutton 2002).

Prior research on nonfinancial data focuses on structured data (i.e., employee headcount, warehouse space) (Brazel et al. 2014), that has organizational rigor and can be analyzed (Huerta and Jensen 2017). In addition to structured nonfinancial data (i.e., employee headcount), more opportunities are arising to transform and analyze unstructured nonfinancial data (Huerta and Jensen 2017), which accounts for 90% of all data (Syed et al. 2013). Such structuring presents an opportunity to identify audit relevant information (Borthick and Pennington 2017; Richins et al. 2017). Unstructured data refers to data lacking organizational rigor (Beath et al. 2012; Davenport et al. 2012), and structuring this data into a format suitable for analysis can be very challenging (Huerta and Jensen 2017). Nevertheless, unstructured data is expected to play a more prominent role in decision making (Richins et al. 2017). Although many companies have been collecting unstructured data, they are uncertain how to effectively leverage this new information source (Earley 2015). For example, the SEC has used satellite imagines to help uncover accounting fraud (SEC 2017).

Language processing tools are now available that can analyze unstructured data such as e-mails, social media postings (i.e., Facebook, LinkedIn, twitter), video surveillance, news videos and cell phone videos (Holton 2009; Vasarhelyi et al. 2015; Raphael 2017; Huerta and Jensen 2017). Deloitte's new tool "Argus' performs text analysis of leases to determine differences in terminology across a population of leases (Raphael 2017). CEOs use of vocal cognitive dissonance markers is associated with a greater likelihood of a restatement (Hobson et al. 2012). Firms use lower levels of pessimistic language in press releases than corresponding MD&A's, as press releases are less regulated (Davis and Tama-Sweet 2012). Poor environmental performers use language that is more optimistic and less certain in their environmental disclosures than strong environmental performers (Cho et al. 2010). Additionally, firms with unusually optimistic disclosures are subject to more litigation (Rogers et al. 2011). Firms with more positive forward looking statements in their MD&A exhibit better current performance, lower accruals, have a lower market-to-book ratio and have lower return volatility (Li 2010). Firms that use more negative words in their annual reports utilize more aggressive tax planning strategies (Law and Mills 2015). Additionally, current earnings is negatively associated with the extent of R&D disclosures (Merkley 2014). Certain linguistic cues are associated with fraudulent financial firm's disclosures, such as more activation language, words, imagery, pleasantness and group references. Such disclosures are of greater length in an attempt to appear more credible; however substantive content included is minimal (Humpherys et al. 2011). Furthermore, tone used in MD&A may be used to predict bankruptcies (Mayew et al. 2015). Finally, the language used in twitter posts is associated with stock price (Sul et al. 2014) and earnings (Bartov et al. 2018).

E-mails are a significant unstructured data source for forensic accounting investigations (Clopton et al. 2014). Analyzing unstructured data, such as e-mails, have been used by regulators during lawsuits and forensic accounting investigations, including the FTC and DOJ (Beach and Schiefelbein 2014; Torpey et al. 2010; Torpey et al. 2009). E-mails may present audit relevant information for identifying missing journal entries (Clopton and Callahan 2017). Analyzing e-mails are not limited to key word searches (Clopton et al. 2014). E-mail tone may be analyzed as well to identify conspiratorial tone (Clopton and Callahan 2017; Ernst and Young 2013).

Despite the advances in data analytics, there are still limitations to their usefulness. The identification of new audit relevant information may be categorized as either violations of business process rules or significant statistical deviations from the steady state of business (Kogan et al. 2014). The identification of an outlier is not a guarantee of an error (Kogan et al. 2014), and data analytics may merely identify false positives (Vasarhelyi et al. 2015; Yoon et al. 2015). Thus, while data analytics may facilitate more effective identification of outliers, these outliers may have a reasonable explanation (Kogan et al. 2014). In certain circumstances analytical procedures may be unable to identify the existence of error or fraud (Cullinan and

Sutton 2002); however, the ability to detect an existing fraud will arguably be more prevalent with the use of data analytics (Smith 2016).

The effectiveness of data analytics will be limited if auditors do not incorporate the findings from these analytics into their decision making process (Davis et al. 1989; Venkatesh et al. 2003). As auditors prefer to rely on simple analytical procedures (Ameen and Strawser 1994; Trompeter and Wright 2010), and data analytics are an advanced form of analytical procedures, auditors may be reluctant to rely on data analytics. Decision makers may not use accounting information when presented to them (Hodge et al. 2004; Janvrin et al. 2013). Information provided by data analytics may be so large that it overwhelms auditors (Brown-Liburd et al. 2015; Issa and Kogan 2014). Although many correlations may be identified, some may represent spurious correlations (Richins et al. 2017). Overwhelming accountants, including auditors, with information hinders decision making (Iselin 1988; Stocks and Harrell 1995; Chewning and Harrell 1990; Simnett 1996; Casey 1980). Thus, while data analytics may be able to identify new audit relevant information, viewing all of this information may hinder auditors' ability to effectively incorporate it into their decision making process and affect their final decisions.

Additional factors that may inhibit auditors' use of data analytics include a client refusing to provide data, not reporting data in a useable format, or providing unreliable data. Auditors' concerns over a data breach may inhibit them from collecting client data (Pentland 2014). Auditors may be reluctant to use data analytics as a previously existing misstatement may be identified. Additionally, subsequent to identifying risks, auditors must perform additional work to examine these risks (AICPA 2017). Auditors' legal liability is higher when a fraud risk is identified but follow up work does not identify fraud, compared to when no fraud risk is identified (Reffett 2010). Thus, auditors may seek to avoid identifying risks in order to minimize litigation risk.

Data Analytical Models

Data analytical models can be grouped into four distinct groups (DHHS 2014). The first type of model is an anomaly model that identifies data exhibiting abnormal patterns compared to the peer group; for example, an anomaly model could identify a credit card with more charges for televisions than 99% of all other credit cards in a single day. The second type of model is a predictive model that analyzes patterns of previously identified issues and compares them to current patterns; for example, a predictive model could compare known characteristics of improper credit card charges and identify new charges with similar characteristics. This is an innovative feature of data analytics, as it allows the models to adapt and independently create new models subsequent to gathering sufficient data (Kuenkaikaew and Vasarhelyi 2013). The third type of model is a rules-based model that identifies data based on predetermined criteria; for example, a rules-based model could a charge for a television in Florida while the cardholder lives in California. The fourth type of model is a network model that performs link analysis; for example, a network model could identify a credit card associated with a phone number that was linked to another card with fraudulent charges (DHHS 2014). Of these four models, a Report to Congress places greatest emphasis on the use of predictive models, specifically stating, “A single predictive model is often as effective as multiple non-predictive models” (DHHS 2015, pg.9).

Prior research on analytical procedures has focused primarily on similar, but less sophisticated, versions of anomaly models (Hirst and Koonce 1996; Asare et al. 2000; Cohen et al. 2000; Glover et al. 2005; Brazel et al. 2009; Brewster 2011). Thus, auditors are experienced with the mental processes required to incorporate the results from anomaly models into their decision making. Anomaly analytical models use a distributional (bell curve) analysis to identify observations that are outliers (i.e., three standard deviations from the mean) in relation to the distribution of other observations (SAS 2014). Examples from the healthcare industry of anomaly models include the following: a provider that bills for a greater quantity of a particular service in a given day than 99% of similar providers in the same area, treating an abnormally high number of patients, performing an abnormally high number of procedures, having a high ratio of patients from outside the practice area, and high patient lengths of stay (DHHS 2014; SAS 2014).

Anomaly models seek to identify an observation that is significantly different from other observations within the same dataset. A limitation of anomaly models is that they may merely identify false positives. For example, a specialist at a teaching hospital that is nationally known may take only extremely complex cases; yet, anomaly detection models would identify this specialist as an outlier and a potential fraudster. Another limitation of anomaly models is that fraudsters may become aware of detection thresholds, and be able to elude detection by remaining just below such thresholds (SAS 2014).

Predictive models offer forward-looking analytics, and provide the potential to identify fraud before it occurs (Kuenkaikaew and Vasarhelyi 2013) and predicting future sales demand or stock performance (Schneider et al. 2015). Predictive models "analyze patterns and past performance in relationships to a particular desired outcome to predict the probability of that outcome" (SAS 2012b, pg. 2). For example, previous frauds can be analyzed, and the strongest variables can be combined into an algorithm and applied to current data to identify otherwise undetectable patterns, which may be indicative of fraud. Predictive models are gaining increased popularity today, and several examples of their applications are discussed in a recent edition of the *Harvard Business Review* (See Figure 2 for examples) (Mankins and Sherer 2014; Mccarthy 2014a; Elton and Arkell 2014; Frick 2014; Choucair et al. 2014; Mccarthy 2014b; Boudreau

2014; McGrath 2014; Reinartz and Rajkumar 2014; Mills 2014; Fox 2014). While predictive analytical models are able to quickly adapt to new schemes, they are limited to identifying fraudulent behavior that is previously known (SAS 2014). By identifying early indicators of fraud before fraud actually transpires, predictive analytics allow organizations to optimize their resources by instituting corrective action before potentially harmful behavior occurs (SAS 2012b; Kuenkaikaew and Vasarhelyi 2013). Within a healthcare setting, predictive models can aid fraud investigators in determining which new clinics are potentially fictitious prior to commencing fraudulent billing. Other models would only be able to identify a clinic *after* the fraud has occurred, and the clinic has potentially shut down, making the collection of the funds much more resource intensive.

Predictive data analytical models can detect fraudulent filings (AAERs) (Dechow et al. 2011; Perols et al. 2017). Predictive data analytical models have identified that firms are more likely to file fraudulent financial statements subsequent to reversing abnormally high accruals (Dechow et al. 2011). Large earnings growth dispersion can be used to predict future restatements of macroecnomic factors (i.e., GDP) by the U.S. Bureau of Economic Analysis (BEA) (Nallareddy and Ogneva 2017). Predictive data analytical models can facilitate asset valuations (Sinclair 2015), and forecasting cash flows interest rates and future revenue changes (Agnew 2016b). There is limited academic research examining whether auditors use predictive data analytical models, which suggests that these models are not commonly used in practice and auditors may not be knowledgeable on how to appropriately use the results from these models.

Theory and Hypothesis Development

Cognitive fit

Cognitive fit is the congruence of the cognitive process used by a decision maker and the underlying decision strategy of a tool used to facilitate decision-making (Vessey and Galletta 1991; Arnold and Sutton 1998; Al-Natour et al. 2008). The Theory of Technology Dominance (TTD) states that a decision maker's reliance on a decision aiding tool is a function of cognitive fit as well as task experience, task complexity and decision aid familiarity (Arnold and Sutton 1998). TTD defines cognitive fit as the "...degree to which the cognitive processes used with the decision aid to complete or solve a task match the cognitive processes normally used by an experienced decision maker" (Arnold and Sutton 1998, pg. 180). Greater cognitive fit between the decision maker and information improves the ease of information acquisition, which in turn leads to greater reliance on information, and quicker and more accurate problem solving (Vessey 1991; Vessey and Galletta 1991; Hampton 2005; van der Land et al. 2012; Tsai et al. 2013; Dunn et al. 2017; Agarwal et al. 1996a). Experience using decision aiding tools improves the decision maker's cognitive fit with the processes used by such tools (Goodhue and Thompson 1995; Dunn and Grabski 2001).

A lack of cognitive fit between the decision maker and the decision aiding tool requires the decision maker to mentally transform the information presented into a useful format. When a decision maker is presented with information that must be mentally transformed into a familiar format that, the decision maker often discsounts or disregards this information (Nisbett and Ross 1980). When a decision maker is not required to mentally tranform information into a format that is useful, it is less mentally taxing, which induces use of the information (Hampton 2005).

Data analtyics may be used as a tool to aid auditors' decision making. When using data analytics to facilitate decision making, the method or process used by that tool influences the cognitive fit between that tool and the decision maker (Vessey and Galletta 1991; Arnold and Sutton 1998; Al-Natour et al. 2008). While the results from anomaly analytical models may be similar or even identical to the results presented from predictive analytical models (for example, stating "data analytics identified this account as being high risk"), the process used to arrive at that conclusion varies significantly. Auditors will experience high levels of cognitive fit when viewing the findings of data analytics that utilize a process with which auditors are experienced using. Thus, cognitive fit will result in increased reliance on the findings of the data analytics when there is congruence between the model and the decision maker (Arnold and Sutton 1998).

When approaching a problem, a decisions maker does not have a blank slate to form mental representations (Agarwal et al. 1996b). Since analytical procedures represent less sophisticated versions of anomaly models, auditors are more familiar with the underlying process used by anomaly models (Hirst and Koonce 1996; Asare et al. 2000; Cohen et al. 2000; Glover et al. 2005; Brazel et al. 2009; Brewster 2011; Brazel et al. 2014). Thus, auditors are expected to exhibit greater cognitive fit when viewing results from anomaly models as compared to predictive models. On the other hand, auditors are expected to experience low cognitive fit when evaluating results from predictive models because the underlying process of these models is not congruent with the decision-maker's model; and low cognitive fit has been shown to reduce decision makers' reliance on tools intended to facilitate decision making (Hampton 2005). As the process similarity of anomaly models is expected to result in greater cognitive fit with the auditor during the risk assessment process, auditors' decisions will be more affected by the results of anomaly models. This leads to the first hypothesis:

H1: Auditors' decisions will be impacted more by unusual activity identified by data analytics using anomaly models as compared to predictive models.

While the use of data analytics is expanding to encompass nonfinancial information, financial information influences decision making more than nonfinancial information (Heyman and Ariely 2004; Mazar et al. 2008; Kouchaki et al. 2013). Yet, nonfinancial measures offer great promise for developing more precise expectations (Brazel et al. 2009; Trompeter and Wright 2010). Examples of nonfinancial measures that may be used to develop more precise expectations include employee headcount, production space, warehouse space, trading volume and retail space (Brazel et al. 2014). Examining financial data in conjunction with nonfinancial data can aid auditors in fraud identification by identifying inconsistencies in client data (Brazel et al. 2009). Yet, auditors only identify such inconsistencies when prompted to do so (Brazel et al. 2014). Auditors' reluctance to use nonfinancial data may be attributable to the costs associated with acquiring and implementing this data. For example, auditors are required to validate underlying data used as part of the audit process (Richins et al. 2017). If auditors are presented with the findings of nonfinancial data, this may mitigate the reluctance to use this data, as the auditors would not need to incur acquiring, implementing nor validating costs. Cognitive fit can be influenced by individual characteristics, such as training and experience (Goodhue and Thompson 1995; Dunn and Grabski 2001). While nonfinancial measures have potential for improving decisions (Messier et al. 2013), auditors are trained and educated to examine primarily financial data and financial statements. Auditors are less accustomed to and less effective at incorporating nonfinancial data into their decision making (Cohen et al. 2000; Brazel et al. 2009; Trompeter and Wright 2010; Brazel et al. 2014). As a result, auditors will have a greater understanding of and better cognitive fit with information presented from data analytical models that use financial data. Thus, auditors' judgments are expected to be influenced more by data analytical models that analyze financial data.

> H2: Auditors' decisions will be impacted more by unusual activity identified from data analytics analyzing financial data as compared to nonfinancial data.

Methods

Participants

Utilizing personal connections, responses from 98 external financial statement auditors who completed an online experiment were obtained and analyzed.[14] Auditors of all ranks use analytical procedures to some extent as part of their job (Trompeter and Wright 2010), and data analytics are an outgrowth of analytical procedures as suggested by the creation of data analytical standards (Appelbaum et al. 2017). Thus, auditors of all ranks are expected to use data analytics to some extent as part of their job. As the data analytical standards developed by the AICPA apply to all auditees (public and private companies of all sizes), firms of all sizes are expected to use data analytics. Thus, any external financial statement auditor was eligible to participate in this study. In order to provide an incentive to complete the experiment, all participants could choose from a list of charities to which a $5 donation would be made on their behalf upon completion of the survey. Participants were randomly assigned to one of four experimental conditions.

Participants averaged 9.0 years of audit experience. Thirty-seven participants (38%) had the title of manager, director or partner. Sixty participants (61%) were employed by national or

[14] Six participants failed manipulation checks. The results presented include all participants, however excluding participants that failed the manipulation checks from the analysis does not change the inferences drawn from this study unless otherwise noted. One participant indicated their intention to decrease budgeted audit hours by 10% in response to the risk identified by the data analytics. This participant was excluded from the analysis.

international sized firms. Seventy-six participants (78%) were CPAs. Fifty participants (51%) audit manufacturing clients, and eighty-two participants (84%) audit privately held clients. Table 2 provides a summary of participants' demographic information.

Experimental Task and Procedure

Using a case adapted from Brazel and Agoglia (2007), participants were told to assume the role of senior auditor for Madison Inc., a privately held mid-sized sporting equipment manufacturer that is a continuing client. Participants were told that they would be tasked with providing a preliminary fraud risk assessment for the current year. Participants were initially provided background information about the client, including information related to Madison's fraud risk assessment, and were informed that fraud risk was initially assessed as "LOW". Participants were informed that the Central Data Analytics Group was used to help in the fraud risk assessment phase of the audit, and were provided additional background information on the Central Data Analytics Group. Participants were informed that the Central Data Analytics Group identified possible unusual activity related to the revenue cycle. Participants received an explanation of the underlying logic of the respective models and the data that was analyzed. Participants were then asked to answer questions regarding fraud risk, budgeted audit hours and reliance. After completing the case, participants completed demographic information and answered manipulation checks.

Independent and Dependent Variables

Two independent variables (the type of data analytical models used and the type of data analyzed to reach this conclusion) were manipulated between participants resulting in a 2 X 2 design. Model type was manipulated by describing the models used by the Central Data

Analytics Group as either anomaly models or predictive models. In the anomaly models condition, participants were told that unusual activity related to revenue was identified by comparing Madison Inc.'s current year activity with the current year activity of other sporting goods manufacturing clients. In the predictive models condition, participants were told that unusual activity related to revenue was identified by comparing Madison Inc.'s current year activity against the activity of a different sporting goods manufacturing client from five years ago when the other company had a material misstatement.

The type of data used by the data analytical models was described as either financial or nonfinancial. For the financial data manipulation, participants were informed that the Central Data Analyzed Group analyzed the ratio of journal entries just below performance materiality to the total number of journal entries (financial information). This ratio was chosen as a major fraud, Healthsouth, began with several fraudulent journal entries just below materiality to avoid auditor detection (Beam 2015; Smith 2016). For the nonfinancial data manipulation, the Central Data Analyzed Group analyzed the ratio of optimistic language in external e-mails to internal e-mails (nonfinancial data). As advances in technology have allowed for unstructured internal data such as e-mails to be analyzed (Warren et al. 2015) and e-mails have been analyzed as part of forensic accounting investigations (Beach and Schiefelbein 2014; Torpey et al. 2009; Torpey et al. 2010), e-mails were chosen for analysis. Optimistic language was chosen to analyze as this type of language differs among companies public filings (Cho et al. 2010; Davis and Tama-Sweet 2012).

To analyze the impact of data analytics on auditors' decisions, three dependent variables were used. The first dependent variable was participants' level of reliance on the data analytics. Reliance was measured using a five item scale adapted from Hampton (2005). Each item was measured on a seven point likert scale. The first item elicited participant's belief that the information identified by the data analytics represents a fraud risk. The second item measured participant's confidence in the accuracy of the information identified by the data analytics related to fraud risk. The third item measured the participant's level of confidence in evaluating fraud risk without the data analytics and was reverse coded. Item four addressed participant's willingness to incorporate the findings from the data analytics into their fraud risk assessment. The final item captured participant's willingness to rely on the findings from the data analytics. To assess the reliability of the measures of reliance, Cronbach alpha was calculated as 0.83, which is above the recommended threshold of 0.70 (Nunnally 1978).[15]

The second dependent variable was fraud risk assessment. Participants were asked to assess the fraud risk level for Madison Inc. on a seven point likert scale with endpoints of "very low fraud risk" and "very high fraud risk" based on the information provided by the Central Data Analytics Group.

The third dependent variable was budgeted audit hours. Using a sliding scale anchored at negative 100% and positive 100%, participants were asked by what percentage they would change budgeted audit hours for revenue from the initial budget of 30 hours.

Results

Identification of potential covariates

Information was collected on participants' experience using data analytics, specifically anomaly and predictive models, as potential covariates. Participants who have experience using

[15] Additionally, composite reliability was calculated as 0.83, which is above the recommended threshold of 0.70 (Fornell and Larcker 1981).

data analytics were asked to respond on five point likert scales regarding how experienced they were at using anomaly and predictive models (with brief descriptions of these models included) with endpoints of “Not at all experienced” and “Extremely experienced”. Analysis of these two questions identified an unexpected and noteworthy finding. A t-test revealed no significant difference (t=0.497) in participants’ experience using predictive models (mean 2.559) as compared to anomaly models (mean 2.590). The argument put forth in the literature review is that auditors will have greater cognitive fit with anomaly models due to more extensive experience; however, this demographic information suggests that use of predictive models may be more prevalent in practice than prior literature suggests. A correlation matrix revealed that participants who do not audit private companies were more likely to have prior experience using data analytics (p=0.061).

Stacked regressions were used to identify potential covariates, as has been done in prior research (Brochet et al. 2014; Blankespoor et al. 2014). Stacked regressions identified prior experience performing fraud risk assessments as a potential covariate for the Fraud Risk Assessment dependent variable (p<0.10). For the Reliance dependent variable, stacked regressions identified participants title, firm size, gender, percent of time auditing manufacturing and private clients, and prior experience using either type of data analytics examined in this study as potential covariates for participants’ reliance on data analytics to aid in fraud risk assessments (p<0.10). Stacked regressions identified the size of the accounting firm the participants was employed by as a potential covariate for budgeted audit hours (p<0.10) and was included as a covariate in the analysis.

Levene’s test revealed that the data does not meet the assumption of homogeneity of variance for the “Fraud Risk Assessment” dependent variable. Homogeneity of variances are not required if ANOVA cell sizes are equal (Field 2009). Consistent with prior research (Lyubimov et al. 2013), a random number generator was used to delete two observations to equalize cell sizes at 24 when testing the hypothesis using the "Fraud Risk Assessment" dependent variable.

Test of Hypotheses

All hypotheses are tested using the three dependent variables discussed above: reliance on the data analytics, fraud risk assessment, and budgeted audit hours. H1 predicts that auditors' judgments will be impacted more by unusual activity identified by anomaly data analytical models as compared to predictive data analytical models. Thus, H1 predicts that auditors will rely more on the data analytics to aid in their fraud risk assessments, make higher fraud risk assessments, and increase budgeted audit hours more when anomaly analytical models identify unusual activity as compared to predictive models. Table 3 Panel A provides descriptive statistics for the reliance dependent variable. None of the potential covariates identified by the stacked regressions were identified as significant covariates. The ANOVA results indicate that participants do not exhibit any differences (p=0.981) in their likelihood to rely on anomaly models as compared to predictive models to aid in fraud risk assessments. Figure 3 Panel A provides a graphical representation the results for reliance.

Table 4 Panel A provides descriptive statistics for the fraud risk assessment dependent variable. Prior experience performing fraud risk assessments was identified as a significant covariate and was included in the analysis.[16] More extensive fraud risk assessment experience is associated with high fraud risk assessments. The descriptive statistics suggest that participants

[16] Prior experience performing fraud risk assessments was not identified as a covariate when only analyzing participants that passed both manipulation check questions.

increase their fraud risk assessment when data analytics have identified unusual activity, regardless of the type of model used and type of data analyzed. In the case provided, fraud risk was initially assessed as low, yet all conditions uniformly increased fraud risk to approximately medium. Table 4 Panel B shows that participants do not exhibit any differences (p=0.825) in their fraud risk assessments when unusual activity is identified by anomaly models as compared to predictive models. Figure 3 Panel B provides a graphical representation of the results for fraud risk assessment.

Table 5 Panel A provides descriptive statistics for budgeted audit hours. The descriptive statistics shows that participants increase budgeted audit hours by approximately 16 percent when data analytics have identified unusual activity, regardless of the type of model used and type of data analyzed. Employer firm size was identified as a covariate and included in the analysis (p=0.015). Examining the correlation between firm size and budgeted audit hours revealed that participants employed by larger firms recommend greater budgeted audit hours in response to unusual activity identified by data analytics. Table 5 Panel B shows that participants do not exhibit any differences (p=0.898) in their judgments to change budgeted audit hours when unusual activity is identified by anomaly models as compared to predictive models. Figure 3 Panel C shows the graphical representation of the results for budgeted audit hours

Taken together the findings from the three dependent variables (reliance, fraud risk assessment and budgeted hours) suggest that anomaly models do not impact auditors' judgments more than predictive models. Thus, H1 is not supported.

H2 predicts that auditors' judgments will be impacted more by unusual activity identified by data analytics that analyzed financial data as compared to nonfinancial data. Thus, H2 predicts that auditors will rely more on the data analytics to aid in their fraud risk assessments, make higher fraud risk assessments, and increase budgeted audit hours more when data analytics analyzed financial data, as compared to nonfinancial data, to identify unusual activity. Table 3 Panel B shows that participants do not exhibit any differences (p=0.163) in their reliance on data analytics that analyzed financial data as compared to nonfinancial data. Table 4 Panel B shows that auditors do not exhibit any differences (p=0.919) in their fraud risk assessments when unusual activity is identified by data analytics that analyzed financial data as compared to nonfinancial data. Table 5 Panel B shows that participants do not exhibit any differences (p=0.237) in their judgments to change budgeted audit hours when unusual activity is identified by data analytics that analyzed financial data as compared to nonfinancial data. Taken together, the findings from the three dependent variables (reliance, fraud risk assessment and budgeted hours) suggest that data analytics that analyze financial data do not impact auditors' decisions more than data analytics that analyze nonfinancial data. Thus, H2 is not supported.

Additional analysis

The interactive effect of the type of data analytical models used and the type of data analyzed on participants' decisions was examined as well. Table 3 Panel B demonstrates that no interactive effect was noted for participants' reliance on data analytics to aid in fraud risk assessments (p=0.571). Table 4 Panel B shows that no interactive effect is noted for participants' fraud risk assessment in response to unusual activity identified by data analytics (p=0.562). Table 5 Panel B shows that the type of data analytical model interacts with the type of data analyzed to impact participants' determination of budgeted audit hours (p=0.015). These results highlight the distinction between auditors' use of data analytics for fraud risk assessments as compared to budgeted audit hours. Increasing budgeted audit hours expresses an intention to investigate a potential risk further, whereas increasing fraud risk suggests that the auditor believes the potential risk is an indicator of fraud risk. Thus, a potential risk must be perceived as riskier in order for auditors to rely on that information and to increase fraud risk as compared to budgeted audit hours.

These results demonstrate that when predictive models are used, participants increase budgeted audit hours more in response to unusual activity identified by analyzing financial data as compared to nonfinancial data. The opposite is true for anomaly models; when anomaly models are used, participants increase budgeted audit hours more in response to unusual activity identified by analyzing nonfinancial data as compared to financial data. These results suggest that auditors' decisions are impacted by the type of model used in conjunction with the type of data analyzed.

Due to the significant interactive effect on budgeted audit hours identified in Table 5 Panel B, simple main effects, while controlling for employer firm size, were examined and are shown in Table 5 Panel C. The results indicate that the type of data analyzed by predictive models significantly impacts participants' budgeted audit hours (p=0.010). When predictive models are used, participants increase budgeted audit hours more when these models analyzed financial data as compared to nonfinancial data. Additionally, the results presented in Table 5 Panel C show that the effect of the type of data analytical models used on budgeted audit hours is impacted by the type of data analyzed. Specifically, when financial data is analyzed by predictive models, participants increase budgeted audit hours more compared to when such data is analyzed by anomaly models (p=0.093).[17] Alternatively, when nonfinancial data is analyzed

[17] Excluding participants that failed manipulation checks results in this finding becoming insignificant (p>0.10).

by anomaly models, participants increase budgeted audit hours more compared to when such data is analyzed by predictive models (p=0.071).[18]

The impact of data analytics on budgeted audit hours is likely attributable to cognitive fit. The crossover effect identified in this study is consistent with prior cognitive fit research (Wheeler and Jones 2003; Speier et al. 2003; Dennis and Carte 1998). Cognitive fit increases with training and experience (Goodhue and Thompson 1995; Dunn and Grabski 2001), thus auditors experience using certain types of data analytics are expected to increase cognitive fit using those models. The use of predictive models in accounting tends to focus on financial data such as accruals, financial performance and earnings dispersion (Beneish 1997; Dechow et al. 2011; Sinclair 2015; Agnew 2016b; Perols et al. 2017; Nallareddy and Ogneva 2017) while the use of predictive models using nonfinancial measures in accounting is limited to abnormal employee reduction and text mining aiding in fraud risk assessments (Holton 2009; Dechow et al. 2011). Thus, when using predictive models, auditors may have more experience, and greater cognitive fit, with such models that analyzed financial data as compared to nonfinancial data. This may explain the simple main effect noted in Table 5 Panel C (p=0.010).

When considering the use of nonfinancial data, prior research focuses on the use of anomaly models compared to predictive models. This is likely attributable to the prominence of unstructured information, and the potential that it has to identify audit relevant information. As previously discussed, unstructured nonfinancial data has been used in prior research primarily to make comparisons against a peer group to identify patterns associated with very high amounts of a certain type of language, suggesting that using nonfinancial data is more commonly analyzed

[18] Excluding participants that failed manipulation checks results in this finding becoming more significant ($p<0.05$).

by anomaly models than predictive models (Cho et al. 2010; Li 2010; Humpherys et al. 2011; Davis and Tama-Sweet 2012; Hobson et al. 2012; Warren et al. 2015; Yoon et al. 2015). This explains auditors' greater increase of budgeted audit hours when nonfinancial data is analyzed by anomaly models compared to predictive models (p=0.071 shown in Table 5 Panel C). Alternatively, considering the analysis of financial data, predictive models focus almost exclusively on analyzing financial data (Beneish 1997; Dechow et al. 2011; Sinclair 2015; Agnew 2016b; Perols et al. 2017; Nallareddy and Ogneva 2017), whereas anomaly models may analyze financial or nonfinancial data (Brazel et al. 2014; Cohen et al. 2000; Glover et al. 2005; Cho et al. 2010; Hobson et al. 2012). The greater focus of predictive models on financial data, as compared to anomaly models, explains auditors' greater increased budgeted audit hours when financial data is analyzed with predictive models compared to anomaly models (p=0.093 as shown in Table 5 Panel C).

Conclusion

The advancement of technology has enabled the development of more sophisticated data analytics that hold the potential to improve the audit process by facilitating analysis of larger datasets of traditional data (Jans et al. 2014; Kogan et al. 2014; Sinclair 2015; Raphael 2017; Jans et al. 2010), along with analysis of new types of nonfinancial data and unstructured data (Warren et al. 2015; PCAOB 2016; Agnew 2016; IAASB 2017). Interest in using more data analytics during the audit process can be seen from the IAASB and PCAOB, as well as a joint initiative by the AICPA and CPA Canada (IAASB 2017; PCAOB 2016; Coffey 2015). Furthermore, the AICPA has developed data analytical standards to replace the analytical procedures guide (AICPA 2015b; Appelbaum et al. 2017; AICPA 2017). Taken together, data analytics are expected to play a more pronounced role in the audit process in the near future. Despite the interest from practice to incorporate data analytics more into the audit process, there is a lack of research examining how auditors use such analytics and whether data analytics impact decisions. Prior research is limited to identifying that auditors are not effective at identifying patterns in data analytics visualizations when viewed before traditional audit evidence (Rose et al. 2017). This study contributes to the literature by providing initial evidence on the impact of different data analytics on auditors' decisions. Inadequate planning to effectively implement data analytics into the audit process may result these tools not being used to their full benefit, and thus a missed opportunity to improve audit quality and effectiveness and create additional value for stakeholders (Sinclair 2015; Agnew 2016b; Raphael 2017; Titera 2013).

The results of this study show that auditors are willing to rely on data analytics to aid in their fraud risk assessments. By relying on the findings of data analytics, auditors demonstrate a willingness to increase fraud risk. The results of this study demonstrate that auditor's reliance on data analytics, fraud risk assessments and budgeted audit hours does not differ by the type of data analytical model used and the type of data analyzed.

Interestingly the interactive effect of the type of data analytical model used and type of data analyzed do impact budgeted audit hours. Auditors budget different audit hours to follow up on a potential risk based on the joint effect of type of model used and type of data analyzed. When auditors view the results of predictive models, budgeted audit hours are greater when these models analyze financial data as compared to nonfinancial data. Yet, the opposite is true for anomaly models; when auditors view the results of anomaly models, budgeted audit hours are greater when these models analyzed nonfinancial data as compared to financial data. This finding is likely attributable to the use of such models in practice. Predictive data analytical models that analyze financial data appear to be more prevalent than predictive models that analyze nonfinancial data. Alternatively, anomaly analytical models that analyze nonfinancial data appear to be more prevalent than anomaly models that analyze financial data.

The results of this study contributes to the cognitive fit literature by demonstrating that cognitive fit influences auditor's budgeted audit hours decisions using data analytics. The results of this study also contribute to the cognitive fit literature by demonstrating that cognitive fit does not always impact reliance. Although the findings related to the joint impact of the type of data analytical model used and types of data analyzed on budgeted audit hours were not hypothesized, examination of demographic data collected and prior research suggest that these findings may be explained by cognitive fit. As no differences in the type of data analytical model used was noted, closer examination of prior research and practice literature suggests that predictive models focus almost exclusively on analyzing financial data as compared to non-financial data, and non-financial data tends to be analyzed using anomaly models. Thus, auditors would be expected to have greater experience analyzing financial data with predictive models compared to anomaly models and greater experience analyzing non-financial data with anomaly models compared to predictive models. As cognitive fit is influenced by users prior training and experience (Goodhue and Thompson 1995; Dunn and Grabski 2001), these differences in experience likely contribute to different levels of cognitive fit and ultimately decision making, which supports the findings of this study related to budgeted audit hours.

As this study is the first to examine auditors' use of data analytics in an experimental setting, there are limitations to this study along with several opportunities for future research. Future research should examine how to effectively induce auditors' reliance on data analytics to improve decisions along with auditors comfort using different types of data analytics (Guénin-Paracini et al. 2014). A limitation of this study is that it only examines the impact of two types of data analytical models that analyzed two types of data on the decision outcome. Future research should examine how the inputs in this study and other inputs impact auditors' decision making processes when using data analytics. Future research should examine auditors' reliance on other types of data analytical models, such as rules-based models and social network analysis (Jans et al. 2014) and analysis of other types of data including structured vs. unstructured nonfinancial data. Future research should seek to examine what combination of data analytical models (for example using anomaly models in conjunction with rules based models) result in the greatest change in auditors' decisions, providing more useful insights than relying on only one type of data (Richins et al. 2017). Future research also may seek to examine the data analytics that auditors choose from when provided with several analytical models options. As data analytics applications can analyze financial and non-financial data, future research may seek to examine how auditors rely on data analytics that analyze financial data in conjunction with nonfinancial data. Future research may also seek to examine decisions for tasks beyond fraud risk assessments and changing budgeted audit hours, for example internal control evaluations. Examining the impact of the accuracy of data analytics on auditors' decisions may present another fruitful opportunity for research.

Another limitation of this study is that the survey was distributed electronically, limiting control over participants. Greater experimental control would require using students in an experimental lab. As this study examines auditor's use of data analytics and draws upon prior audit experience to make judgments, using student participants would not be appropriate. Thus, although experimental control may have been compromised on some participants, practicing auditors were necessary for this study. Another limitation is that demographic information revealed that predictive data analytical models are used more commonly in practice than prior research suggests. This casts doubt upon the external validity of the research and practice articles cited in the literature review regarding auditors' use of data analytics. Thus, future research should seek to examine how data analytics are commonly used during the audit process.

Effective implementation of data analytics will likely consist of substantial implementation costs. Such costs will likely be passed on to clients through the audit fee. Thus, future research should examine how audit fees will change as a result of implementing data analytics into the audit process. Also, future research should investigate under what circumstances auditees are willing to accept a greater audit fee, and what persuasion tactics auditors may employ in order to ensure a sustained relationship with the client in light of such fee increases.

Future research should seek to examine differences in forensic and internal auditors' use of data analytics compared to financial statement auditors. Different regulatory oversight regimes (i.e., PCAOB) or personality traits might result in using different data analytics. Future research may also seek to examine how prior fraud experience impacts auditors' decisions using data analytics to aid in fraud risk assessments. Finally, future research may seek to examine how data analytics will impact the auditing profession's knowledge development. While reducing the technical skills required to use technology enabled tools increases reliance on such tools, relying on data analytics may result in de-skilling of auditors, and ultimately hindering advancement of auditing knowledge.

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STUDY THREE: THE IMPACT OF THE HUMAN FACTOR ON AUDITOR'S RELIANCE ON DATA ANALYTICS

Introduction

Auditors' use of analytical procedures has received considerable attention in the prior academic literature (Cohen et al. 2000; Knapp and Knapp 2001; Glover et al. 2005; Brazel et al. 2009; Trompeter and Wright 2010; Glover et al. 2015). Advances in technology have enabled analytical procedures to move beyond ratio analysis and unusual fluctuations, and to emerge into more advanced forms, including population testing of supporting data (Jans et al. 2014; Gray and Debreceny 2014; Alles 2014; Titera 2013; Murphy and Tysiac 2015; Richins et al. 2017; Jans et al. 2010), predictive modeling (Kuenkaikaew and Vasarhelyi 2013; Statistical Analysis System (SAS) 2014; Krahel and Titera 2015) and analysis of non-financial data (Warren et al. 2015). These technology enabled analytics are referred to as data analytics. Data analytics encompass analytical procedures historically used by auditors (Appelbaum et al. 2017; Titera 2013), as well as business intelligence and analytics techniques using applications grounded in data mining and statistical analysis (Chen et al. 2012). The capability and use of data analytics in accounting is greatly expanding in practice (Deloitte 2010; DHHS 2012; KPMG 2012; PriceWaterhouseCoopers 2013; AICPA 2015; Coffey 2015; Ernst and Young 2015a); These data analytics may fundamentally change the audit process, which may greatly reduce the distinction between analytical procedures and substantive testing (Jans et al. 2014). However, how to ensure effective use of these tools as part of the audit process is unclear.

Despite the promise to improve audit effectiveness (Davenport and Harris 2007; Titera 2013), research examining the impact of data analytics on auditors' decisions is scant (Brown-Liburd et al. 2015; Appelbaum et al. 2017). Prior research on data analytics is limited but shows that auditors are not effective at identifying patterns in data analytics visualizations when viewed before traditional audit evidence (Rose et al. 2017). Even when similar technologies provide information deemed to be 100% accurate, auditors are reluctant to rely on these technologies due to fear of litigation (Sutton et al. 1995). In some instances, auditors have had adverse reactions to technology, such as disengaging with audit tasks (Bamber and Snowball 1988) and working around the technology (Bedard et al. 2003; Bedard et al. 2007; Dowling and Leech 2014). The mere existence of such technology-based tools is insufficient to improve decision making, as no improvement is noted when such tools are not used (Venkatesh et al. 2003; Davis et al. 1989; Rose et al. 2017; Huerta and Jensen 2017). Auditors may not use such tools due to factors such as fear of litigation (Sutton et al. 1995), cognitive processing limitations (Brown-Liburd et al. 2015) or lack of trust in technology (Lee and See 2004). Thus, despite the advances in technology and the ability of data analytics to identify outliers that auditors previously would not have been able to identify (Alles and Gray 2015; Alles 2014; Murphy and Tysiac 2015), the availability of data analytics does not guarantee that auditors will rely on these findings during their decision making process, constraining and undermining the potential benefits.

The purpose of this study is to examine auditors' reliance on data analytics under varying levels of risk when the results are presented by another human as opposed to a system. Humans are often reluctant to rely on, and are less trusting of, technology as compared to another human to perform a given function (Waern and Ramberg 1996; Lewandowsky et al. 2000); yet, it is unclear if this difference in trust is still present as technology plays a more prominent role in society. While auditors historically had the required skillset to perform analytical procedures (Hirst and Koonce 1996; Cohen et al. 2000; Trompeter and Wright 2010; Brazel et al. 2014), more sophisticated exploratory data analytics will likely require more advanced analysis capabilities and technical skills (Richins et al. 2017; Huerta and Jensen 2017). Public accounting firms may choose to introduce data analytics into the audit process by incorporating data analytics software into their audit software. Auditors would be responsible for performing the data analytics themselves. Alternatively, some firms are using data scientists to perform and present the data analytics (Ernst and Young 2015a; Agnew 2016a; Richins et al. 2017). Given that the level of trust in the data analytics may differ depending on the source (software or data scientist), research is needed to ascertain if and when the source of the analytics matters.

This may be a particularly important issue as the level of risk increases within an audit. Prior research suggests that auditors are reluctant to rely on analytical procedures as the level of risk identified increases (Glover et al. 2005). Auditors place greater reliance on information that suggests a low risk of material misstatement. Auditors' reluctance to rely on information that identifies an audit risk potentially undermines the ability to identify a material misstatement. Examining whether reliance on data analytics decreases as risk increases can provide insight into the impact of data analytics on auditors' decisions. When prior information provided by a particular source has been subject to errors, relying on current information from the same source is accompanied by increased risk of making an error. This increased risk results in decreased reliance on the information by the decision maker. The decrease in reliance is greater when information is provided by a system as compared to another human (Lewandowsky et al. 2000). Thus, the source of the information as well as the level of risk may interact to alter the impact of either source or level of risk.

Using the Theory of Trust, auditors are predicted to trust data analytics more when presented from another human as opposed to a system. Trust entails willingness to be vulnerable to actions of another party without the ability to actively monitor or control that party (Mayer et al. 1995). Decision makers are more trusting of human sources as compared to technology source (Waern and Ramberg 1996; Lewandowsky et al. 2000), and this trust results in reliance (Muir 1989; Lerch and Prietula 1989; Lee and See 2004). Thus, auditors are expected to rely more on the results of data analytics when presented from another human as compared to a self-generating system. Auditors are less likely to rely on information suggesting a high rather than low risk (Glover et al. 2005). Thus, auditors are predicted to rely more on data analytics that identify a low risk. Decision makers rely more consistently on information provided by another human as compared to technologies (Lewandowsky et al. 2000). Thus, when a high risk is identified by data analytics, a decrease in reliance is expected to be more pronounced when it was identified by a technology than by a human. Therefore, the level of risk identified is predicted to moderate the impact of presentation source on auditors' reliance on the data analytics.

Using an experimental setting, ninety-two auditors were informed that the findings from data analytics were communicated by either another human (a data scientist) or a self-generating system (a data analytics software) and if the findings suggest a high or low risk of material misstatement. The results of this study indicate that neither the presentation source nor level of risk identified affects auditors' reliance on data analytics. Interestingly, the two variables have an interactive effect on reliance on data analytics. When a self-generating system presents the findings of data analytics, auditors are more likely to rely on the analytics when a high risk is identified as compared to a low risk. The opposite is true when another human presents the findings of the data analytics, as auditors are more likely to rely on the analytics when a low risk of misstatement is identified as compared to a high risk of misstatement.

The results of this study contribute to research and practice alike. The results of this study are timely and important given the heightened interest in using data analytics throughout the audit process as highlighted by the AICPA and CPA Canada (Coffey 2015), the IAASB (IAASB 2017) the AICPA's development of data analytical standards (AICPA 2015b; Appelbaum et al. 2017), and PCAOB staff (PCAOB 2016). The results of this study demonstrate that factors impacting auditor's reliance on data analytics should not be considered in insolation, as reliance may not be impacted by individual items, however reliance is impacted when factors are considered together. The results present evidence on the effectiveness of firms developing a data scientist group as compared to training individual auditors on how to use software to run data analytics. As the results suggest that auditors are more likely to rely on a high risk when presented from a self-generating system, this study calls into question the effectiveness of developing a data scientist group, as auditors may be reluctant to rely on risks identified by this group. This study contributes to research by providing experimental evidence to the limited literature on auditors' use of data analytics.

The remainder of this paper will be comprised of four sections. The next section discusses insights from the academic literature into the use of data analytics and the use of technology. Section three discusses the research method. The following section discusses the results of this study. The final section presents concluding remarks.

Background and Hypotheses Development

Data Analytics

Data analytics have the potential to facilitate auditors' decision making, and improve the audit process (Moffitt and Vasarhelyi 2013; Appelbaum et al. 2017), ultimately improving audit efficiency and effectiveness (Brown-Liburd et al. 2015; Titera 2013). The AICPA has expressed interest in increasing the use of data analytics in the audit process (Coffey 2015), as demonstrated by the Assurance Services Executive Committee (ASEC) developing an “Audit Data Analytics Guide” (Appelbaum et al. 2017) to replace the current Analytical Procedures Guide. Replacement of the Analytical Procedures Guide with the Data Analytics Guide suggests that data analytics can be viewed as an outgrowth and expansion of analytical procedures (Appelbaum et al. 2017), and analytical procedures are a subset of data analytics (AICPA 2015a; Titera 2013). The IAASB Data Analytics Working Group (DAWG) serves a similar purpose to the AICPA’s ASEC committee. The DAWG is examining how to effectively use data analytics during the audit process to enhance audit quality and to examine revising international accounting standards to permit the use of data analytics during the audit process (IAASB 2017). The use of data analytics is on the rise for many Fortune 500 companies’ internal audit departments (Rose et al. 2017).

Advances in technology have enabled the development of the aforementioned data analytics and the expansion of analysis capabilities in accounting (Trompeter and Wright 2010; Jans et al. 2014; Warren et al. 2015; Appelbaum et al. 2017). Technological advances have contributed to decreased costs to record and store data, ultimately increasing the size of datasets that can be analyzed (Brown-Liburd et al. 2015; Mcmillan and Barr 2015). Datasets have grown to the extent that traditional software tools are not able to effectively capture, store, manage and analyze the information (McKinsey 2011). Data analytics have emerged from analytical procedures and include more sophisticated anomaly modeling (Thiprungsri and Vasarhelyi 2011), population testing capabilities (Vorhies 2013; Kogan et al. 2014; Jans et al. 2014; Alles 2014; Gray and Debreceny 2014; Murphy and Tysiac 2015; Titera 2013; Jans et al. 2010), predictive modeling (Rose 2013; Wilkinson 2013; Kuenkaikaew and Vasarhelyi 2013; SAS 2014; DHHS 2014; Krahel and Titera 2015), cluster analysis (Thiprungsri and Vasarhelyi 2011), process mining (Jans et al. 2010; Jans et al. 2013; Jans et al. 2014) and nonfinancial data analysis including video, audio and text (Warren et al. 2015). Effectively utilizing these analytics may prove to be challenging for auditors, as data analytics require a specialized skillset that auditors typically do not possess (Ernst and Young 2015a; Agnew 2016a; Richins et al. 2017). Thus, while analytical procedures can be performed within an audit team (Hirst and Koonce 1996; Cohen et al. 2000; Trompeter and Wright 2010; Brazel et al. 2014), utilizing data analytics is more likely to require utilizing resources, such as data scientists, outside of the traditional audit team (Ernst and Young 2015a; Agnew 2016a; Richins et al. 2017).

Introducing data analytics into the audit process can potentially help auditors identify new audit relevant information (Jans et al. 2014; Kogan et al. 2014), reduce labor intensive tasks and focus time on more judgment intensive tasks (Brown-Liburd et al. 2015) and high risk areas (AICPA 2015a). This may minimize the risk that a material misstatement exists but was not identified, enhancing audit quality and effectiveness and creating more value for audit stakeholders (Agnew 2016b; Raphael 2017; Titera 2013). Data analytics may also improve fraud prevention and detection initiatives (Brivot and Gendron 2011; Jans et al. 2014; Titera 2013; Jans et al. 2010). A former CFO of Healthsouth, a large fraud that has received attention from the academic literature (Jones et al. 2008; Chung et al. 2008; Brazel et al. 2009; Free and Murphy 2015; Glover et al. 2015), stated that the fraud would have been identified much earlier had these data analytical tools been used during the Healthsouth audit (Smith 2016).

Prior research focuses on the capabilities of data analytics (Kogan et al. 2014; Jans et al. 2014; Jans et al. 2010); however, prior research on data analytics impacting auditors' decisions is limited to identifying that auditors are not effective at identifying patterns in data analytics visualizations when viewed before traditional audit evidence (Rose et al. 2017). As data analytics can be viewed as an outgrowth of analytical procedures, insights on auditors' use of data analytics can be obtained by examining auditors' use of analytical procedures. Analytical procedures during planning influence auditors' extent, breadth, depth, and focus of substantive testing (Asare et al. 2000), and facilitate more effective fraud risk assessments (Knapp and Knapp 2001). Analytical procedures impact auditors' risk assessments more for high risk clients (O'Donnell and Schultz 2005). Deficiencies in auditors' use of analytical procedures have been identified by the PCAOB (PCAOB 2007a; PCAOB 2007b; PCAOB 2008); the PCAOB has cited deficiencies in the audit work of all the big four firms (PCAOB 2011a; PCAOB 2011b; PCAOB 2014a; PCAOB 2014b). As data analytics may be viewed as an outgrowth of analytical procedures (Appelbaum et al. 2017), these deficiencies may persist when auditors use data analytics. Professional standards mandate the use of analytical procedures during the planning and review phase of an audit; however, auditors often use analytical procedures during substantive testing as well (Trompeter and Wright 2010; Appelbaum et al. 2017).

As data analytics have been enabled by technology, examining auditors' use of data analytics warrants consideration of auditors' utilization of technology. There are several benefits to human-technology collaboration such as increased consistency and accuracy (Riley 1994; Liebl and Roy 2003; Markoff 2012), reduced costs (Riley 1994; Brynjolfsson and McAfee 2014) and freeing humans from time-consuming and labor-intensive activities (Parasuraman and Riley 1997). Despite the potential benefits of human-technology collaboration, these benefits may go unrealized if the technology is not used properly (Alles and Gray 2015). Adopting such tools is hindered when they require advanced technical skills (Alles 2015), requiring involving the IT department, report obsolete information and produce reports difficult to understand (Huerta and Jensen 2017). Effective implementation of these tools require support from management, including a willingness to change how they do business (Kiron et al. 2014; Ferguson 2014; Fitzgerald 2014).

Technology enabled tools can be used to facilitate and support audit work (Winograd et al. 2000; Banker et al. 2002; Dowling and Leech 2007). Without proper implementation, technology may have adverse implications such as underuse (lack of reliance), misuse and abuse (Parasuraman and Riley 1997; Dzindolet et al. 2003; National 2014). Thus, the mere existence of tools such as data analytics is not a guarantee that auditors will perceive them as trustworthy, rely on them, and ultimately incorporate the information identified into their decision making. Furthermore, the amount of information provided by data analytics may overwhelm auditors and exceed their processing capacity, which has been shown to impede decision making (Iselin 1988; Kleinmuntz 1990). Thus, process capacity limitations may constrain the full benefits of data analytics from being realized (Brown-Liburd et al. 2015). For example, although data analytics may identify high risk audit areas (Brown-Liburd et al. 2015), and allow auditors to spend more time and effort on tasks that require human judgment (AICPA 2015a), auditor processing weaknesses and cognitive limitations may prevent these benefits from human-technology collaboration to be realized (Brown-Liburd et al. 2015).

Trust and Technology

Analytical procedures have historically been performed within audit teams (Trompeter and Wright 2010). More sophisticated data analytics (i.e., predictive modeling and cluster analysis) may require a skillset beyond what most audit teams have, thus the analysis may be conducted by a data analyst or data scientist (Ernst and Young 2015a; Agnew 2016a; Richins et al. 2017). Alternatively, auditors may utilize a software to perform data analysis, as such technologies are used to facilitate the audit process (Dowling and Leech 2014; Dowling and Leech 2007). The source of the results of the analytics warrants consideration, as the results may be presented directly from a software utilized by the auditor (a technology), or a data scientist (another human). Reliance on the information provided by the software or data scientist is contingent upon an auditor's trust in the information source. Even when providing the same information and demonstrating the same level of competence, humans trust information provided by other human sources more than technology sources, and this trust has been shown to influence decision making (Sheridan and Verplank 1978; Sheridan 1980; Waern and Ramberg 1996; Lewandowsky et al. 2000). Tools used to facilitate decision making, such as data analytics, can greatly improve decisions (Hale and Kasper 1989). A lack of trust in an automated technology tool is accompanied by decreased reliance on the technology (Muir 1989; Lerch and Prietula 1989; Lee and See 2004). As data analytics have been enabled by technology, consideration of auditors' trust in technology is warranted when considering reliance on these analytics.

Mayer et al. (1995) puts forth the Theory of Trust, and defines trust as "The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al. 1995, pg. 712). Vulnerability exists when some level of risk is present by trusting information provided from another party and direct observation of the other party is impractical (Mayer et al. 1995). Thus, the need for trust only arises in risky situations (Mayer et al. 1995).

Trust in technology results in use of (reliance on) technology (Muir 1989; Lerch and Prietula 1989; Lee and See 2004), confidence in the technology, and ultimately results in better decisions (Waern and Ramberg 1996; Lewandowsky et al. 2000; Hoffman et al. 2013). When there is a lack of trust in technology, human users will experience frustration and attempt to avoid relying on the technology (Koopman and Hoffman 2003; Hoffman et al. 2008). A lack of trust in technology results in misuse (the user inappropriately relying on the technology) and disuse (the user refusing to rely on the technology) (Lee and See 2004), which ultimately hinders performance (Sorkin and Woods 1985; Wickens et al. 2000). Despite the potential benefits of the data analytics previously discussed, auditors' lack of trust in and reliance on data analytics will cause these benefits to go unrealized. A lack of trust in technology may cause auditors to have adverse reactions to the technology, including disengaging with audit tasks (Bamber and Snowball 1988) and attempting to work around the technology (Bedard et al. 2003; Bedard et al. 2007; Dowling and Leech 2014).

Although different sources (human or technology) may have the same competency level and provide identical information, trust in the information provided may still vary (McGinnies and Ward 1980). Thus trust in the source presenting the results of the data analytics is expected to influence auditors' reliance on the information provided. As decision makers trust information provided by humans more than technology sources (Lewandowsky et al. 2000), and trust increases reliance (Muir 1989; Lerch and Prietula 1989), the following hypothesis is presented regarding auditors' reliance on data analytics as influenced by the source of information:

> H1: Auditors will rely more on data analytics provided by another human than data analytics that are self-generated from a system.

Risk Identified

Trust is influenced by contextual factors such as the perception and actual level of risk involved, the balance of power and alternatives available to the decision maker (Mayer et al. 1995). Trust in information is influenced by the complexity of the decision making process required by relying on the information (Simmell 1964; Lewis and Weigert 1982; Luhman 1982). Trust in information increases when it reduces complexity in the decision making process (Lewis and Weigert 1982), suggests proceeding with a simple course of action, suggests no issues identified, or confirms expectations arising from previously obtained information (Simmell 1964; Luhman 1982). When information suggests proceeding on a complex course of action there will be a reduction of trust, making it less likely that the decision maker will incorporate the information into their decision making (Simmell 1964).

Trust impacts decision making only when some level of uncertainty is present (Lewis and Weigert 1982; Mayer et al. 1995; Tomkins 2001). Accordingly, as decision uncertainty increases trust in information used to make the decision decreases (Lewis and Weigert 1982; Kramer 1999). An example of a setting where such uncertainty exists is during the audit process when auditors must consider the risk that procedures performed did not detect an existing material misstatement (Guénin-Paracini et al. 2014, 2015; Westermann et al. 2015). As previously stated, information that suggests a complex action is deemed less trustworthy by decision makers (Luhman 1982). In response to identifying a risk of material misstatement, auditors are required to consider the complex task of changing the nature, timing, and extent of substantive procedures.[19] Thus information identifying a risk of misstatement requiring complex follow up actions will likely be deemed less trustworthy by auditors.

While using analytical procedures can help auditors assess a risk of a material misstatement (see AS 2305) or fraud (Knapp and Knapp 2001; Smith 2016), this does not guarantee that the auditor will identify an actual misstatement (Cullinan and Sutton 2002). When analytical procedures identify information indicative of a possible misstatement, auditors may be reluctant to rely on this information (Glover et al. 2005). Auditors rely more on the findings of analytical procedures when the results suggest that the information being examined is fairly stated and there is a low risk of material misstatement. This suggests that auditors are reluctant to rely on findings of analytical procedures that require the complex task of changing substantive testing and performing additional work (Glover et al. 2005). This is likely attributable to the increase risk of improperly changing substantive process to increase the amount of follow up work required. Furthermore, when analytical procedures identify an unusual fluctuation, auditors rely on explanations suggesting that the fluctuation is not the result of an error (Bedard and Biggs 1991; Asare et al. 2000) and thus less complex follow up work is necessary.

As data analytics are an outgrowth of analytical procedures (Appelbaum et al. 2017), difference in auditors' decisions when relying on analytical procedures are expected to persist when relying on data analytics. Thus, as auditors are reluctant to rely on analytical procedures that suggest a heightened risk of material misstatement (Glover et al. 2005), auditors are expected to be reluctant to rely on data analytics that suggest a heightened risk of a material

[19] Specifically, AS 2301.09 states "the auditor should design and perform audit procedures in a matter that addresses the assessed risk of material misstatement due to error or fraud for each relevant assertion of each significant account and disclosure"

misstatement. Auditors are expected to trust and rely on information from data analytics that do not present a risk of material misstatement (and do not require complex follow-up decisions) more than information that presents a risk of material misstatement. Thus, the following hypothesis is presented:

> H2: Auditors will rely more on data analytics that indicate a low risk of misstatement than a high risk of misstatement.

Data analytics offer expanded opportunities for identification of audit relevant information (Jans et al. 2014; Brown-Liburd et al. 2015), however performing this analysis is likely beyond the skillset of traditional audit teams (Ernst and Young 2015a; Richins et al. 2017). In order to compensate for this, organizations may rely on employees with a non-audit skillset, such as data scientists, to perform more sophisticated data analysis and provide the findings to the audit team (Ernst and Young 2015a; Agnew 2016a; Richins et al. 2017). At times, information provided from another source (human or technology) may contain an error (Waern and Ramberg 1996; Lewandowsky et al. 2000). When information provided by another source contains an error, a breach of trust results. This breach of trust results in decreased reliance on the information source, however when the information source is a technology, reliance decreases more than when the information source is another human. Thus, when a human provides information that is not accurate and there is a breach of trust, the decrease in reliance will not be as great as when a technology breaches trust (Lewandowsky et al. 2000). This suggests that information provided by a human will be relied on more consistently under different environmental contexts than information provided by technology (Lewandowsky et al. 2000). The willingness to continue to rely on other humans may be attributable to the ability to share blame with another source in the event an incorrect decision is made (Whyte 1991; Lewandowsky et al. 2000).

After viewing information that contains an error, a human presentation source results in more consistent future reliance than a technology presentation source (Lewandowsky et al. 2000). When the results of data analytics do not present a risk that requires the complex task of consideration of changing substantive procedures, there is a lower risk of making an error. Thus, the source presenting a low risk is not expected to have a significant impact on auditors' reliance on this information. When a high risk is identified, a decrease in reliance is expected. As information presented by another human is relied on more consistently and less subject to contextual factors (Lewandowsky et al. 2000), this decrease is expected to be more pronounced when presented by a technology. Thus, when technology identifies a risk that requires a complex decision making process, auditors are expected to rely less on this information. This hypothesis is formally stated as:

> H3: The level of risk identified by the data analytics will moderate the effect of the presentation source such that auditors will rely less on the findings of data analytics identifying a high risk of misstatement when the information comes from a system rather than a human.

Method

Participants

Personal connections were utilized to obtain and analyze responses from 92 external financial statement auditors that completed an online experiment.[20] As the data analytic

[20] Of the 110 auditors that completed the experiment 64.55% of participants failed at least one manipulation check. Thus excluding all participants that failed manipulation checks would result in excluding a substantial portion of the sample and would limit any inferences drawn from this study. The results presented in the remainder of this study contain the responses of the 92 participants that passed at least one manipulation check.

standards state that public and private companies stand to benefit from these standards, auditors from all size firms and all types of clients were eligible to participate. Furthermore, auditors of all ranks use analytical procedures as part of their job (Trompeter and Wright 2010), and as data analytics can be viewed as an outgrowth of analytical procedures (Appelbaum et al. 2017), auditors of all ranks will be expected to use data analytics as part of their job. Thus, auditors of all ranks employed by any size firm were eligible to participate in this study. As the task required prior experience performing control risk assessments, participants were required to have prior experience performing control risk assessments.

Participants were randomly assigned to one of four experimental conditions. Participants averaged 3.2 years of audit experience with a range of 0.5 years to 20 years. Forty seven participants (51%) had the title of supervisor, manager or director. Thirty nine participants (42%) were employed by national or international firms. Seventy eight participants (85%) were CPAs. Table 6 provides a summary of the participants' demographic information.

Experimental Task and Procedures

To test the hypothesis proposed above, a 2X2 experiment manipulating the presentation source of the results of data analytics (a human versus a system) and the level of risk identified (high versus low) as the independent variables was distributed to participants. Across all experimental conditions, participants were told that upper level management has begun to pilot test using data analytics on low risk audit areas of low risk engagements. Participants were informed that their client, Omega computer parts, has been selected by upper management for this program. Participants were informed that as part of planning the audit, data analytics would be used to help assess the risk of material misstatement in a historically low risk account, accounts payable. Accounts payable was chosen as the audit area to apply the data analytics because this area has been examined in previous data analytics research (Jans et al. 2014; Kogan et al. 2014) and the AICPA has developed a guide for accounts payable (AICPA 2018).

Participants were informed that process mining was used to analyze the accounts payable cycle, as process mining can identify audit relevant information (Jans et al. 2010; Jans et al. 2013; Jans et al. 2014). Process mining is the comparison of actual processes against designed processes, and can identify the frequency of predetermined steps not occurring sequentially (Jans et al. 2014). Participants were informed that the following predetermined steps should occur sequentially, (1) create a purchase order, (2) sign a purchase order, (3) release a purchase order, (4) receive goods, (5) receive invoice, and (6) pay invoice.

Independent and Dependent Variables

To manipulate presentation source, participants were informed that the findings of the data analytics applied to accounts payable were communicated by either a software, or the firm's internal data scientist. A data scientist was chosen as the human presenting the results as firms are developing data scientist groups (Ernst and Young 2015a; Agnew 2016a; Deloitte 2018).[21] While data scientists may not have strong accounting domain specific knowledge, they are able to perform more sophisticated exploratory analysis than accountants are capable of conducting (Richins et al. 2017); yet, accountants are likely better able to leverage this information (Kaplan 2006). Thus, in the data scientist condition, participants do not have any interaction with the data analytics software. Alternatively, in the software condition, participants were informed that they conducted the analytics on their firm's software.

[21] Additionally, job postings for data scientists were noted on all of the big 4's websites.

To manipulate risk, participants were informed that the findings of the data analytics identified either a high or low risk of a material misstatement. Participants were provided a message describing the results of the analytics, which stated that the percentage of checks written in relation to invoices received suggests a high or low risk of misstatement. They were informed that the data analytics only presents the raw data analysis and does not incorporate financial statement audit knowledge. Participants were asked on a seven point Likert scale the likelihood that they would increase the level of control risk above low.[22]

To measure the dependent variable of reliance, the reliance scale created by Hampton (2005) was adapted. The scale consists of five items and is and items are measured using a seven point Likert scale. The first item measures participant's agreement with the information identified by the data analytics. The second item measures participant's confidence in the accuracy of the findings of the data analytics. The third item measures the participant's preference to making audit decisions without the data analytics and is reverse coded. Item four addresses participant's willingness to incorporate the findings from the data analytics into their decision making. The final item captures participant's willingness to rely on the findings of the data analytics. In addition to the five item measures, a question regarding participants' trust in the information provided was added to the reliance measure. To assess the reliability of the measures of reliance, Cronbach alpha was initially calculated as 0.78 which is above the recommended threshold of 0.70 (Nunnally 1978). Although above the recommended threshold of 0.70, examination of the items making up the reliance variable revealed that the third item did

[22] As a result of the high manipulation check failure rate noted in footnote 2, a t test was used to compare the means of the likelihood to increase control risk between the high and low risk conditions. Results suggest that participants understood the manipulation (p=0.014). Additionally, an ANCOVA examined the differences between groups and corroborated that the manipulation was effective (p=0.008).

not correlate highly with the other items. As prior research discards items not loading properly (Hampton 2005), the third item was excluded from the analysis. The five remaining item measures are highly correlated with a Cronbach alpha of 0.90.[23]

Participants were asked to assess the likelihood that fraud has occurred in the accounts payable process. This variable was measured on a seven point Likert scale with endpoints of "Not at all likely" and "Extremely likely".

Finally, participants finished by answering demographic questions and manipulation checks. A potential covariate of participant's self-confidence effectively incorporating data analytics into the audit process was measured as well. Self-confidence was measured as this has been shown to influence decision maker's trust in and reliance on technology (Muir and Moray 1996). This variable was measured using a 7 point Likert scale adapted from Lewandowsky et al. (2000). Including this variable in the analysis does not change the inferences drawn from this study.

Results

Identification of potential covariates

A correlation matrix was examined to identify the existence of any covariates and differences between conditions. Participant's age was identified as potential covariates for the Reliance dependent variable. Participant's prior experience using data analytics was identified as a potential covariate for participant's likelihood of fraud assessments. Examination of

[23] Prior research has found that excluding items that do not correlate with other items is appropriate (Hampton 2005). Thus, the third item was excluded from the analysis.
Additionally, composite reliability was calculated at 0.90, which is above the recommended threshold of 0.70 (Fornell and Larcker 1981).

conditions revealed more males in the System condition (p=0.017) and more CPAs in the High Risk condition (p=0.060). These variables were included in the results presented only when they were identified as significant (p<0.10).

Test of Hypotheses

All hypotheses were tested using the primary Reliance dependent variable. Table 7 Panel A provides descriptive statistics for the reliance dependent variable. While all participants indicate a willingness to rely on data analytics, reliance is greatest when a self-generated system presents a high risk, and lowest when a data scientist presents a high risk. Participants' age was identified as a covariate (p=0.078), such that younger participants were more likely to rely on the data analytics. H1 predicts that auditors will rely more on data analytics provided by another human than data analytics that are self-generated from a system. As shown in Table 7 Panel B, the ANCOVA results suggest that auditors do not exhibit any difference (p=0.523) in their likelihood to rely on data analytics presented by another human than data analytics that are presented by self-generated from a system. H2 predicts that auditors will rely more on data analytics that indicate a low risk of misstatement than a high risk of misstatement. As shown in Table 7 Panel B, the ANCOVA results suggest that auditors do not exhibit any difference (p=0.726) in their likelihood to rely on data analytics that identify a low risk of misstatement as compared to a high risk of misstatement. H3 predicts that the level of risk identified by the data analytics will moderate the effect of the presentation source such that auditors will rely less on the findings of data analytics identifying high risk of misstatement when the information comes from a system rather than a human. Although Table 7 Panel B shows an interactive effect of these two variables (p=0.052), it is not the hypothesized moderation. Thus, the moderation effect hypothesized in H3 is not supported.

The interactive effect suggests that auditors are more likely to rely on data analytics presented from a self-generating system when a high risk of misstatement is identified as compared to a low risk of misstatement. Alternatively, auditors are more likely to rely on data analytics presented from another human when a low risk of misstatement is identified as compared to a high risk. These findings suggest that auditors are more likely to rely on a system when more extensive follow-up work is required. Alternatively, auditors are more likely to rely on another human when less extensive follow up work is required. See Figure 4 Panel A for a graphical representation for the results for the Reliance dependent variable.

Additional Analysis

Participants indicated the likelihood that they believe fraud occurred based on the findings of the data analytics. Participant’s prior experience using data analytics as part of the audit process was identified as a significant covariate (p=0.003) and was included in the analysis. Greater prior experience using data analytics is associated with a higher assessment of the likelihood that fraud had occurred. See Table 8 Panel A for descriptive statistics for the likelihood of fraud variable. As shown in Table 8 Panel B, the ANCOVA results suggest that the level of risk identified by the data analytics (p=0.268), the source of the analytics (0.221), and their interactive effect (p=0.168) do not impact auditors’ assessments of the likelihood of fraud. Figure 4 Panel B provides a graphical depiction of the results. Results of a planned contrast presented in Table 8 Panel C demonstrate that auditors perceive the likelihood of fraud as lowest when viewing the results of data analytics presented by a self-generating software that presents a low risk (p=0.028).[24] Thus, auditors would be least likely to increase fraud risk when results of data analytics are presented by a self-generating system that presents a low risk.

Conclusion

Advances in technology have enabled auditors' analytical procedures to move beyond traditional measures of ratio analysis and have enabled more advanced forms of analysis including population testing of supporting data (Alles 2014; Gray and Debreceny 2014; Jans et al. 2014; Richins et al. 2017; Huerta and Jensen 2017; Jans et al. 2010), predictive modeling (Kuenkaikaew and Vasarhelyi 2013; SAS 2014; Krahel and Titera 2015) and analysis of unstructured data (Vasarhelyi et al. 2015; Warren et al. 2015). Although the use of data analytics in accounting is expanding (Deloitte 2010; DHHS 2012; KPMG 2012; PriceWaterhouseCoopers 2013; AICPA 2015a; Coffey 2015; Ernst and Young 2015a), there is limited research examining auditors' use of these tools (Brown-Liburd et al. 2015; Rose et al. 2017). Yet, auditors have expressed interest in increasing the use of technology enabled tools as part of the audit process (Lowe et al. 2017). Although data analytics have the potential to improve auditors' decisions (Davenport and Harris 2007), these benefits will not be realized if auditors are reluctant to rely on these tools.

The results of this study contribute to the literature by providing initial evidence on auditor's reliance on data analytics. Prior literature on auditors' use of data analytics is limited to identifying that auditors are not effective at using data analytics to identify patterns when

[24] Examination of variances revealed that the Likelihood of Fraud variable had unequal variances. As equal variances are not required when ANCOVA cell sizes are equal, using the process outlined in Lyubimov et al. (2013), participants were excluded using a random number generator to create equal cell sizes. The results remain qualitatively unchanged, except for the significant planned contrast results noted are no longer significant.

presented before traditional audit evidence (Rose et al. 2017). The results of this study suggest that while the presentation source and level of risk identified do not result in different levels of reliance on the findings of data analytics individually, together these two variables may impact auditors' reliance on data analytics. Specifically, auditors appear more likely to rely on data analytics presented from a self-generating system when a high risk is identified as compared to a low risk. The opposite appears to be true for auditors' reliance on data analytics presented from another human, as reliance is greater when a low risk is identified compared to a high risk. As firms should be most concerned with a lack of reliance when a high risk is identified, the results of this study suggest that having a data analytics group may not be as effective at inducing reliance as training auditors to use a software on their own. Additionally, when viewing the findings of data analytics that suggest a low risk of misstatement and is presented from a self-generating system, auditors' assess the lowest likelihood that fraud has occurred.

This study also contributes to the theory of trust literature (Mayer et al. 1995) and the trust in technology literature (Waern and Ramberg 1996; Lewandowsky et al. 2000). Technology has advanced and has become more prominent in society (Liburd-Brown et al. 2015), which may influence decisions makers' familiarity and trust in technology. Thus, future research is needed to examine how advances in technology have impacted humans trust in technology and if the findings from prior research on trust in technology still hold today.

As with any research study, these findings are subject to limitations and present opportunities for future research. Although a substantial portion of the auditors in this study's sample were employed by regional and local firms, the difference in use of technology enabled tools among firm size is diminishing (Lowe et al. 2017). As Lowe et al. (2017) does not specifically examine data analytics, future research may seek to examine how different size firms are implementing data analytics. This study only examines one type of data analytics, process mining, examining one audit area, accounts payable. Thus, future research may seek to examine other types of data analytics, such as predictive modeling (Kuenkaikaew and Vasarhelyi 2013; SAS 2014; Krahel and Titera 2015) and network analysis (Jans et al. 2014). Future research may also seek to examine auditors' use of data analytics that analyze non-financial and unstructured data. The advancement of technology enabling language processing tools now allow for text analysis (Yoon et al. 2015); thus, examining auditors' use of the findings of these tools may provide avenues for future research. Future research may seek to examine how error rate of data analytics impact reliance on these tools, as expertise of the trustee has been shown to influence the trustor's trust in that party (Hovland et al. 1953; Good 1988; Lieberman 1981). Finally, future research should examine how data analytics impact other audit tasks such as changing budgeted audit hours. As trust has been shown to change with increased interaction (Boyle and Bonacich 1970; Kee and Knox 1970), future research should seek to examine the impact interaction with the data analytics has on reliance.

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GENERAL CONCLUSION

The three studies presented in this dissertation explore the impact of data analytics on auditors' judgments. Study One examines an attempt to structure the audit process for nonprofessionalized auditors using data analytics. As Study One identifies that presenting nonprofessionalized auditors with data analytics may result in detrimental implications, Study Two and Study Three examine the impact that data analytics have on financial statement auditors' judgments. Study One highlights the importance of using professional, as opposed to nonprofessionalized auditors, to audit high risk areas identified through data analytics. Study Two examines the impact that different data analytical models that analyze different types of data have on auditors' judgments. Study Three examines the impact of the presentation source on auditor's judgments under varying levels of identified risk. The following paragraphs discuss the contributions of each of the aforementioned studies from a theory and/or practice perspective.

The results of Study One highlight the importance of using professional auditors to perform follow up audit procedures on high risk audit areas identified through data analytics. While using data analytics may allow for auditors to focus their time on the highest risk areas (Liburd-Brown et al. 2015), the statistical outliers identified may have justifiable explanations (Kogan et al. 2014). The results of this study highlight the use of nonprofessionalized auditors acting in a professional capacity. The auditors examined in this study do not meet the criteria of professionals as demonstrated by the lack of expertise, certification, and professional judgment of these auditors and the adverse impacts their actions ultimately can have on society. The adverse societal implications attributable to these nonprofessionalized auditors demonstrate the need for professional auditors to review high risk areas identified through data analytics.

Dirsmith et al. (2015) argues that the accounting profession is becoming increasingly de-professionalized (). With the rise of data analytics in the public accounting domain (Coffey 2015; IAASB 2017; Appelbaum et al. 2017), it may even seem viable to structure the audit process sufficiently through guidance from data analytics to allow nonprofessionals to adequately perform audits. The results of this study highlight several adverse societal implications from utilizing nonprofessionalized auditors in a critical audit setting. This study warns against using nonprofessionalized auditors to audit high risk areas identified through data analytics. Society would likely be better off if the accounting profession was to actively seek a reversal of the de-professionalization trend (Dirsmith et al. 2015) and ensure that professionals are performing associated audit procedures over high risk areas identified through data analytics. Although this study examines a group of healthcare fraud auditors, several shortcomings of implementing data analytics into the audit process have been identified that may manifest in a financial statement audit setting.

Although the procedures utilized in this study relate to healthcare regulatory fraud auditors who are not drawn from the audit profession, it is unclear if external financial statement auditors will also incur difficulties in properly using and interpreting data analytics. The results of the first study set the foundation for the remaining two studies in this dissertation to examine the impact data analytics have on external financial statement auditors' judgments.

The results from Study Two highlight the importance of considering the type of data analytical model used in conjunction with the type of data analyzed. While data analytics uniformly impact fraud risk assessments, utilizing different types of data analytics results in auditors changing budgeted audit hours by different amounts. When predictive data analytical models are used, auditors increase budgeted hours more when such models analyze financial data as compared to nonfinancial data. The opposite is true when anomaly data analytical models are used, as auditors increase budgeted hours more when nonfinancial data is analyzed as compared to financial data. Additionally, the results of this study reveal that auditors' use of predictive modeling is more prevalent in practice than prior research suggests.

The results from Study Two have important implications for audit practice, as they suggest that understanding auditors' use of data analytical models should not be considered in isolation. While auditors' may not exhibit a difference in incorporating the results of data analytics that use a type of model, or analyzed a type of data, considering these two factors together result in different judgments. By highlighting the joint effect of the type of data analytical model and data analyzed on auditor's judgments, this study lays the foundation for future research on the types of data analytics that may impact auditors' judgments.

While Study Two examines only two types of data analytical models that analyzed two types of data, there are many other variations of data analytical models and types of data that auditors may utilize that can be examined in future research. Future studies should examine auditor's use of other types of data analytical models, including rules-based and social network models (Jans et al. 2014) in addition to analysis of other types of data. As Study Two highlights the joint effect of data analytical models and data analyzed, future research may seek to examine the impact of other combinations of these variables.

The results of Study Three indicate that auditor's reliance on data analytics are not impacted by the presentation source or level of risk identified. Yet, the results reveal that the joint effect of presentation source and level of risk identified impact auditor's reliance on data analytics. When the findings of data analytics are presented by another human, auditors rely more on findings that suggest a low risk than a high risk. The opposite is true when the findings of data analytics are presented by a self-generating system, as auditors rely more on findings that suggest a high rather than a low risk.

The results from Study Three have implications for audit practice, as they suggest that the development of data scientist groups by accounting firms to introduce data analytical skills into audit teams may not be the most effective method of inducing reliance on the analytics from auditors. Data analytics can help auditors focus their time on higher risk areas that require more judgment intensive tasks (Liburd-Brown et al. 2015). The results suggest that such benefits will not be realized when high risk areas are presented from a data scientist. Firms should reevaluate the development of data scientist groups, as the results of this study suggest that training individual auditors to use data analytic software is more effective at inducing reliance on high risks.

Study Three examines the presentation source and level of risk identified by the data analytics using analysis called process mining. Future studies should seek to examine how other types of data analytics impact auditor's judgments. Future research may seek to examine how increased experience using data analytics impacts auditors' reliance on these data analytics. As past error rates have been shown to influence judgments (Good 1988; Lieberman 1981), future research may seek to examine how the past error rates of analytics impacts reliance on data analytics.

In summary, the results reported in this dissertation suggest that data analytics impact auditors' judgments. Understanding auditor's use of data analytics is an emerging area with prior research limited to demonstrating that auditors are only effective at incorporating the results of data analytics visualizations when viewed later in the audit process (Rose et al. 2017). By presenting empirical evidence of the use of data analytics in the audit domain, these studies contribute to our understanding of judgment and decision-making. This dissertation highlights the importance of using professional auditors to assess risks identified by data analytics. Furthermore, not all data analytics uniformly impact auditors' judgments. Thus, merely providing a decision maker with the findings of data analytics may not result in the desired outcome.

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APPENDIX A: STUDY 1 FIGURES

Background of respondents:

1. Please tell me about your job, what you do and what your responsibilities are.
2. What has been your background leading up this point? How did you get to your current job?
3. What is your current title? May I have a business card?
4. How long have you been in this position?

Control items:

1. Can you tell me about what kind of provider you are? (ex: hospital, SNF, physician's office)
2. How many beds do you have? What is the breakdown between SNF, NF, ALF, IL, etc.
3. What county and state are you located in?
4. Is the organization a Non-profit or For-profit provider?
5. Can you talk to me about the level of competition you face in your operating area. (occupancy rates, payer mix, referrals, etc.).

ZPIC Audits:

1. Can you tell me what you know or have heard about ZPIC audits?
2. Can you tell me how and if you changed your activities (corporate compliance, education and training provided to staff) to prepare for them? Are you preparing differently from previous investigations?
3. Can you describe the ZPIC audit(s) experience? (the number of audits, if you received any advance notice, the number of auditors, how long the process was, resources used)
4. Can you tell me how long were they on site for? How much of your time did they require? How did you deal with their requests?
5. Can you tell me what the timeframe was from notice of the ZPIC audit until they showed up and until any issues were resolved? How does this compare to previous investigations?
6. How would you characterize your discussion with the ZPIC auditors? Can you tell me how the ZPICs treated your employees? Were they demanding, accommodating or considerate of your time?
7. Can you tell me if and how you have responded to the ZPIC investigation? Have you done anything differently after the fact? What did you and your colleagues learn from this experience?
8. Can you tell me what you think the likelihood is of them returning?
9. What were the primary issues that the ZPICs brought up? What were their primary findings? Can I see one of the documents that you received? (***Remind the organization to redact resident identifying information***).
10. Can you tell me if you faced any penalties or fines? If so what were they?
11. Can you tell me about the most challenging part of the audit and why it was so challenging?
12. Can you tell me what documents do they usually look at? Can I see one that you were cited on?

13. Can you tell me to whom do they communicate their findings to? Is it a formal report? Who receives the report? Are there different versions. Would you share any of the documents with me?

Societal impact:

1. Have you experienced any unexpected to unanticipated consequences from the ZPIC audit?
2. Has the ZPIC audit impacted the individuals/communities you serve?
3. Did the quality of care change during and after the ZPIC audit?
4. What do you think would happen to the elderly in your region if you went out of business?
5. Did the ZPIC audit put any financial hardship on your organization? Do you think a ZPIC audit could result in bankruptcy?
6. What do you think most of your patients would do if your organization did not exist? What other HC options are available to the community? How could the community be impacted by this lack of service?

Third parties influencing a change in behavior:

1. Did any third parties (external auditors, attorneys, consultants, etc.) give you any notice or warnings about the ZPICs?
2. Did third parties (external auditors, attorneys, consultants, etc.) help you prepare for the ZPICs? Did they provide any advice or counsel for preparation?
3. Did third parties (external auditors, attorneys, consultants, etc.) help you respond to the ZPICs? Did they provide any advice or counsel for response?
4. How would you have liked third parties (external auditors, attorneys, consultants, etc.) to have helped you prepare and respond to the ZPICs?

Leverage, negotiation:

1. Do you have any ability to negotiate with the ZPIC auditors? How does this compare to previous fraud investigators?
2. How would you describe the relationship with your external auditor?
3. How would you describe the relationship with your ZPIC auditor, and previous fraud investigators?
4. Does your relationship with the ZPICs differ from previous healthcare auditors?

After being in the industry for several years, do you think the average provider (not you, someone else) could exert leverage on the ZPICs?

Figure 1 – Interview Protocol

Table 1 – Study 1 participants demographic information

#	Job title	Subindustry	ZPIC came on site	Fines[6]	Hot spot region[3]	Financial Statement Auditor Size	Non-profit
1	Manager in the revenue cycle	Hospital	No	No	No	International	Yes
2	Owner	SNF[1]	Yes	Yes	Yes	Regional[4]	No
3	CEO	Hospice	No	No	No	National	Yes
4	Director in care management department	Hospital	No	No	No	International	Yes
5	CEO	Hospice	Yes	Yes	Yes	National	Yes
6	Financial Director (CFO equivalent)	SNF[1]	Yes	Yes	Yes	Regional	Yes
7	CFO	Hospice	N/A[2]	N/A[2]	Yes	Regional	Yes
8	Nurse consultant	Home Health	Yes	Yes	No	Local	No
9	Chief Compliance Officer	DME[5]	Yes	Yes	No	National	No
10	Owner	Home Health	Yes	Yes	No	Local	No
11	CEO	Home Health	Yes	Yes	No	Anonymous	No
12	Executive Director	Home Health	Yes	Yes	No	Local	No
13	CEO	Home Health	Yes	Yes	No	National[4]	No
14	Owner	DME[5]	Yes	Yes	Yes	N/A	No
15	Clinical administrator	Home Health	Yes	Yes	No	National[4]	No
16	Chief Compliance Officer	Home Health	Yes	Yes	Yes	N/A	No
17	President	Home Health	Yes	Yes	No	National[4]	No
18	Owner	Dr. Office	No	Yes	No	Local[4]	No
19	Chief Operating Officer	DME[5]	Yes	Yes	No	National[4]	No
20	CEO	DME[5]	Yes	Yes	No	National	No
21	CEO	Home Health	Yes	Yes	No	Local	No
22	Administrator	Dr. Office	Yes	Yes	No	Regional[4]	No
23	Director in the revenue cycle	Hospital	No	No	No	International	Yes
24	Director of Compliance	Home Health	Yes	Yes	No	Local	No
25	Director of Nursing	Home Health	Yes	Yes	Yes	Anonymous	No
26	Clinical Care Coordinator	Home Health	No	Yes	Yes	Local	No
27	Director of Nursing	Home Health	No	Yes	Yes	Local	No
28	Administrator	Home Health	Yes	Yes	Yes	N/A	No
29	CFO	Home Health	No	Yes	Yes	Local	No
30	Owner	Home Health	No	Yes	Yes	Local	No
31	Chief Operating Officer	Home Health	No	No	No	Anonymous	No
32	CEO	Home Health	Yes	No	No	National	No
33	Agency director	Home Health	Yes	Yes	No	National	Yes
34	CEO	Home Health	Yes	Yes	No	Local	No
35	Director of Clinical services	Home Health	No	Yes	Yes	Local	No
36	Owner	Home Health	No	Yes	No	Local[4]	No

1- SNF represents a Skilled Nursing Facility, commonly known as a nursing home

2- During the interview, the interviewee revealed that they did not have a ZPIC investigation. The interviewer proceeded with the interview to inquire of the participants perspective abou the ZPIC audits based on what they understood other providers have experienced.

3- Hot Spot Region refers to if the provider has at least one location in one of the nine designed hot spots for Medicare fraud (Department 2012)

4- Some participants did not have an external financial statement audit, however they had consultant or tax work performed by a CPA firm

5- DME represents a Durable Medical Equipment company

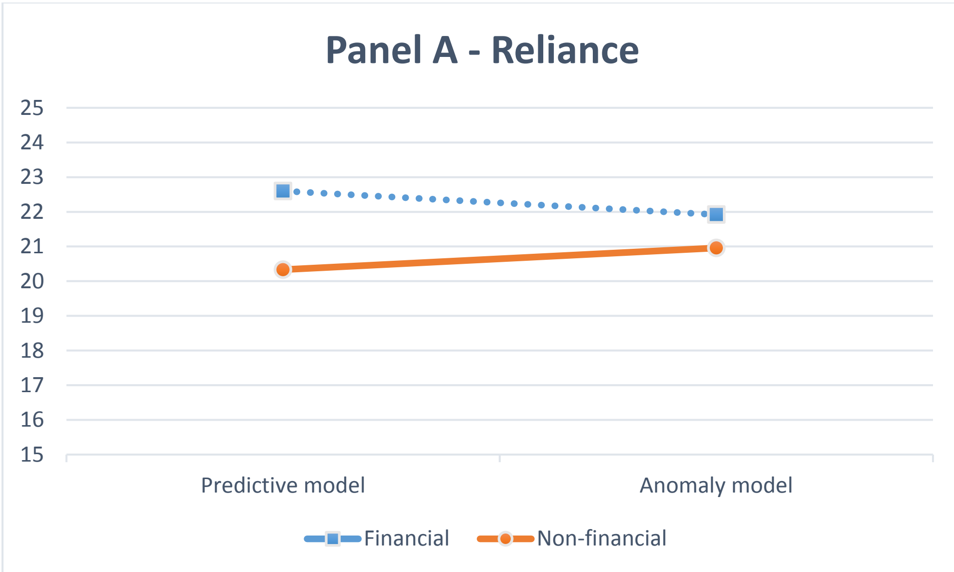
6- All fines were related to documentation, none were fraud related

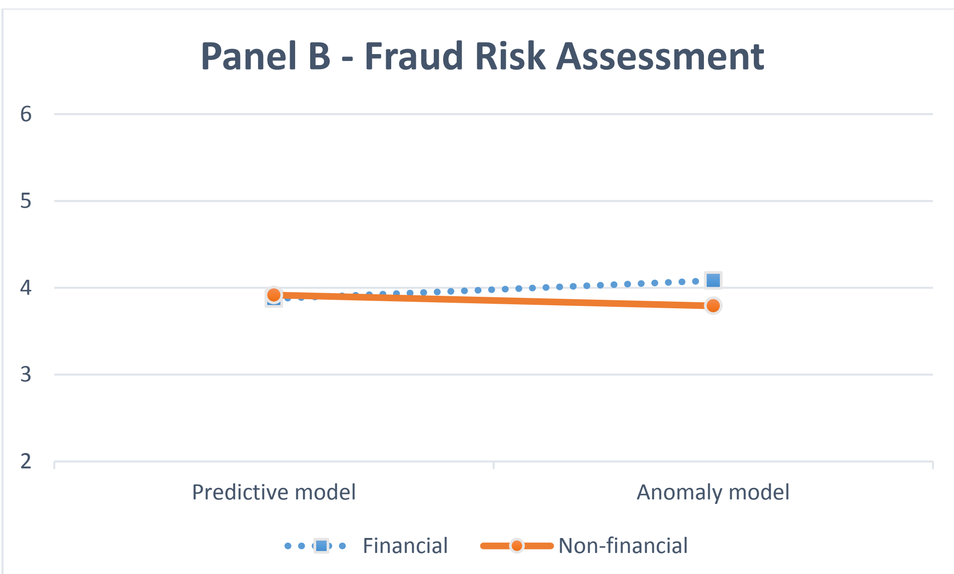
Note: More than one individual from some of the providers were interviewed

APPENDIX B: STUDY 2 FIGURES

Author	Title	Use
Rita McGrath	**To Make Better Decisions, Combine Datasets**	**Reduction in funding to NYC Parks and Recreation tree pruning caused tree-injury claims to soar**
John Boudreau	**Predict What Employees Will Do Without Freaking Them Out**	**Google determined when employees are most likely to quit, offered those employees "new career roles"**
Werner Reinartz and Rajkumar Venkatesan	**Track Customer Attitudes to Predict Their Behaviors**	**Predict returning customers based on behavior**
Bechara Choucair, Jay Bhatt and Raed Mansour	**How Cities are Using Analytics to Improve Public Health**	**Chicago Department of Public Health (CDPH) use to assign risk scores for inspections**
Karen Mills	**Use Data to Fix the Small Business Lending Gap**	**Banks Small Business lending**
Michael Mankins and Lori Sherer	**A Process for Human-Algorithm Decision Making**	**Optimizing decisions on what collection accounts to pursue**
Walter Frick	**Finding Entrepreneurs Before They've Founded Anything**	**Identify entrepreneurs that will likely start a company**
Jeanne Harris and Mark McDonald	**What the Companies That Predict the Future Do Differently**	**Identify manufacturers' machines that are about to fail so can be replaced and not disrupt production**
Brian McCarthy	**Beware the Analytics Bottleneck**	**Increase sales**
Justin Fox	**When a simple Rule of Thumb Beats a Fancy Algorithm**	**Predicting customer behavior**
Brian McCarthy	**Integrate Analytics Across Your Entire Business**	**Identify key performance indicators**
Jeff Elton and Simon Arkell	**Create a Strategy That Anticipates and Learns**	**Help doctors identify people at risk of developing certain diseases**

Figure 2 –Predictive models in use outside of accounting from the Harvard Business Review


Panel A - Reliance
25
24
23
22
21
20
19
18
17
16
15
Predictive model
Anomaly model
Financial
Non-financial


Panel B - Fraud Risk Assessment
6
5
4
3
2
Predictive model
Anomaly model
Financial
Non-financial

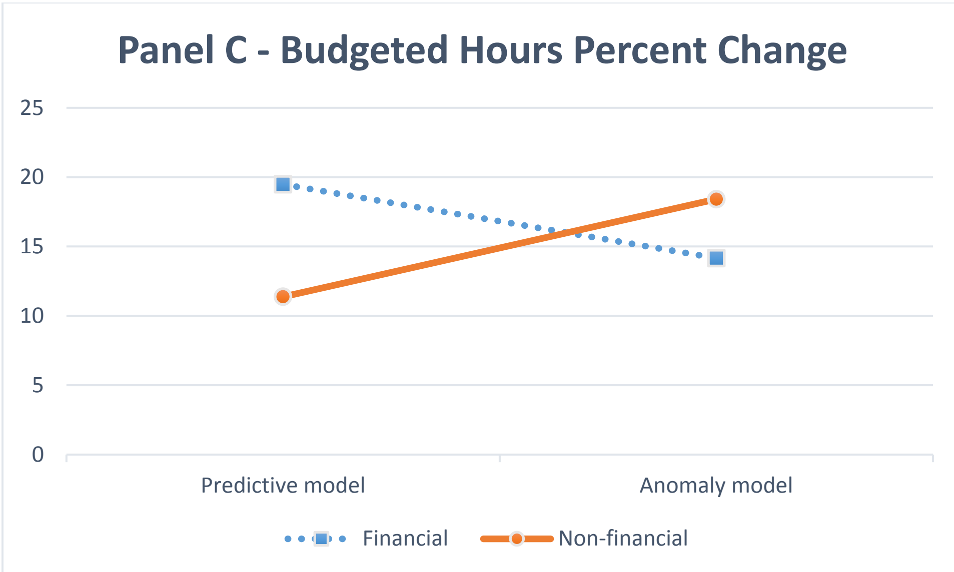


Figure 3 – Graphical depiction of results of study 2

APPENDIX C: STUDY 2 TABLES

Table 2 – Demographic profile of study 2 participants (n=98)

Panel A			
Gender		n	%
	Male	62	63.3%
	Female	36	36.7%
Title			
	Staff	22	22.4%
	Senior	32	32.7%
	Supervisor	7	7.1%
	Manager	19	19.4%
	Director	4	4.1%
	Partner	14	14.3%
Firm size			
	Local	11	11.2%
	Regional	27	27.6%
	National	25	25.5%
	International	35	35.7%
Audit manufacturing clients			
	Yes	50	51.0%
	No	48	49.0%
Audit privately held clients			
	Yes	82	83.7%
	No	16	16.3%
Experience using data analytics			
	Yes	59	60.2%
	No	39	39.8%
Experience performing fraud risk assessments			
	Yes	92	93.9%
	No	6	6.1%

Panel B					
		TITLE			
		Predictive		**Anomaly**	
		n	%	n	%
Financial	Staff	6	24.0%	6	24.0%
	Senior	7	28.0%	6	24.0%
	Supervisor	1	4.0%	0	0.0%
	Manager	5	20.0%	6	24.0%
	Director	2	8.0%	1	4.0%
	Partner	4	16.0%	6	24.0%
Nonfinancial	Staff	5	20.8%	5	20.8%
	Senior	8	33.3%	11	45.8%
	Supervisor	3	12.5%	3	12.5%
	Manager	5	20.8%	3	12.5%
	Director	0	0.0%	1	4.2%
	Partner	3	12.5%	1	4.2%
		FIRM SIZE			
		Predictive		**Anomaly**	
		n	%	n	%
Financial	Local	2	8.0%	6	24.0%
	Regional	11	44.0%	3	12.0%
	National	4	16.0%	8	32.0%
	International	8	32.0%	8	32.0%
Nonfinancial	Local	3	12.5%	0	0.0%
	Regional	6	25.0%	7	29.2%
	National	8	33.3%	5	20.8%
	International	7	29.2%	12	50.0%

Table 3 – Results of study 2 Reliance variable

Panel A - Descriptive Statistics - Reliance mean [standard deviation]

	Type of Model		
Type of Data	**Predictive model**	**Anomaly model**	**Overall**
Financial	**22.600**	**21.920**	**22.260**
	[5.635]	**[5.514]**	**[5.528]**
	n=25	**n=25**	**n=50**
Nonfinancial	**20.333**	**20.958**	**20.646**
	[6.404]	**[5.086]**	**[5.730]**
	n=24	**n=24**	**n=48**
Overall	**21.490**	**21.449**	
	[6.069]	**[5.276]**	
	n=49	**n=49**	

Panel B: ANOVA Results

Source of variation	df	MSE	F-Statistic	p-value
Type of Model	**1**	**0.019**	**0.00**	**0.981**
Type of Data	**1**	**63.809**	**1.98**	**0.163**
Types of Model*Type of Data	**1**	**10.427**	**0.32**	**0.571**
Error	**94**	**32.235**		

Dependent variable is the Reliance scale adapted from Hampton (2005). The reliance dependent variable is the total score of five questions answered on 7 point likert scales. These questions measure participants 1) agreement with the information identified by the data analytics, 2) confidence in the accuracy of the findings of the data analytics, 3) confidence to evaluate fraud risk without the analytics (reverse coded), 4) willingness to incorporate the findings from the analytics into their decision making, 5) willingness to rely on the findings of the data analytics. The total Reliance score may range from 5 to 35. The means are reported in Panel A.

The Type of Model was manipulated by varying whether the participants was told the Central Data Analytics Group used Anomaly models (Type of Model=1) or Predictive models (Type of Model=0). Type of Data was manipulated by varying whether the Central Data Analytics analyzed financial data (Type of Data=1) or nonfinancial data (Type of Data=0).

Table 4 – results of study 2 Fraud Risk Assessment variable

Panel A - Descriptive Statistics - Fraud Risk Assessment mean [standard deviation]

	Type of Model		
Type of Data	**Predictive model**	**Anomaly model**	**Overall**
Financial	**3.875**	**4.083**	**3.979**
	[1.262]	**[1.100]**	**[1.176]**
	n=24	**n=24**	**n=48**
Nonfinancial	**3.917**	**3.792**	**3.854**
	[0.776]	**[1.021]**	**[0.899]**
	n=24	**n=24**	**n=48**
Overall	**3.896**	**3.938**	
	[1.036]	**[1.060]**	
	n=48	**n=48**	

Panel B: ANCOVA Results

Source of variation	**df**	**MSE**	**F-Statistic**	**p-value**
Type of Model	**1**	**0.052**	**0.05**	**0.825**
Type of Data	**1**	**0.011**	**0.01**	**0.919**
Types of Model*Type of Data	**1**	**0.357**	**0.34**	**0.562**
FRExp	**1**	**6.426**	**6.10**	**0.015**
Error	**91**	**1.053**		

Dependent variable "fraud risk" is measured on a 7 point likert scale with endpoints of "Very low fraud risk" and "Very high fraud risk". The means are reported in Panel A.
The Type of Model was manipulated by varying whether the participants was told the Central Data Analytics Group used Anomaly models (Type of Model=1) or Predictive models (Type of Model=0). Type of Data was manipulated by varying whether the Central Data Analytics analyzed financial data (Type of Data=1) or nonfinancial data (Type of Data=0).
FRExp is measured on a 5 point likert scale with endpoints of "Not at all experienced" and "Extremely experienced".

Table 5 - Results of study 2 Budgeted Audit Hours variable

Panel A - Descriptive Statistics - Change in Budgeted Audit Hours mean [standard deviation]

	Type of Model		
Type of Data	**Predictive model**	**Anomaly model**	**Overall**
Financial	19.480	14.160	16.820
	[14.021]	[9.616]	[11.820]
	n=25	n=25	n=50
Nonfinancial	11.375	18.417	14.896
	[9.458]	[11.769]	[11.146]
	n=24	n=24	n=48
Overall	15.510	16.245	
	[12.567]	[10.827]	
	n=49	n=49	

Panel B: ANCOVA Results

Source of variation	df	MSE	F-Statistic	p-value
Type of Model	1	13.224	0.02	0.898
Type of Data	1	90.671	1.42	0.237
Types of Model*Type of Data	1	935.576	6.20	0.015
Size	1	752.275	6.12	0.015
Error	93	122.890		

Panel C: Follow-Up Tests of Simple Effects controlling for employer Size

Source of variation	df	MSE	F-Statistic	p-value
Effect of Type of Model on nonfinancial data	1	409.033	3.33	0.071
Effect of Type of Model on financial data	1	353.780	2.88	0.093
Effect of Type of Data on predictive models	1	843.339	6.86	0.010
Effect of Type of Data on anomaly models	1	101.252	0.82	0.366

Dependent variable is the percent change in budgeted audit hours. Participants used a slider scale ranging from -100% to 100% to select their answer. The means are reported in Panel A.
The Type of Model was manipulated by varying whether the participants was told the Central Data Analytics Group used Anomaly models (Type of Model=1) or Predictive models (Type of Model=0). Type of Data was manipulated by varying whether the Central Data Analytics analyzed financial data (Type of Data=1) or nonfinancial data (Type of Data=0).
Size measures the size of the accounting firm the participant is employed by. Local firms are measured as 1, regional firms as 2, national firms 3, and international firms as 4.

APPENDIX D: STUDY 2 EXPERIMENTAL MATERIALS

BACKGROUND

Assume that you are the audit senior (in-charge) assigned to the 12/31/17 fiscal year-end audit of Madison Inc. The audit team consists of you (the senior auditor), two staff, a manager, and a partner. Madison Inc. is a domestic privately held, mid-sized manufacturer of sporting goods equipment. It makes a variety of products for baseball, football, hockey, basketball, hunting, and fishing. Its products are sold across the U.S. to retailers of sporting goods equipment and directly to customers via its internet website. Your firm has audited Madison Inc. for the last five years and past audits have always resulted in unmodified (i.e., clean) audit opinions. As in the prior year, the partner-in-charge of the Madison Inc. audit has set overall audit risk for the 2017 audit at “Low”.

Assume it is October 2017 and you are currently in the planning phase of the 12/31/17 fiscal year-end audit.

TASK OBJECTIVE

Based on the information provided in this case, you will be asked to prepare for the fraud brainstorming session for Madison. During this session, fraud risk will be assessed and changing budgeted hours will be considered for the revenue cycle in conjunction with any identified risks for the current year (12/31/17) Madison Inc. audit. It is important that you respond to questions in this case study as you normally would during your day-to-day activities.

Background of Revenue cycle

Inherent risk has been set at “MEDIUM” in all of Madison’s previous audits.

Control Risk for the revenue cycle for the 2017 Madison Inc. audit has been assessed as “LOW”. Madison Inc. relies largely on adequate separation of duties and proper authorization of transactions to meet internal control objectives. Internal controls overall are very effective. No significant control issues have been noted during previous audits.

Performance materiality for the 2016 audit was calculated as $301,000. Performance materiality for the current year (2017) audit was calculated as $304,000.

Considerations for Fraud Risk Assessment:

Fraud risk has been set at “LOW” for all of Madison’s previous audits. Several factors contributed to initially assessing Madison’s fraud risk as “LOW” in the current year audit including:

- No significant incentives/pressures, opportunities or rationalizations by management have been identified for committing fraud.
- Experience with the client indicates that top management of Madison Inc. is fairly conservative in terms of reporting financial results.

- No factors appear to exist that might motivate them to circumvent or override existing control procedures.
- The sporting goods industry is experiencing steady market trends.
- Madison has reported stable profitability over the past five years and exceeds all debt covenants by substantial amounts.
- There are no significant financial interests in Madison from the Board of Directors or Management.
- Your firm has a good working relationship with Madison.

Assume that over the past ten years all of your firm's clients have granted your firm permission to collect non-identifiable data to be used for data analysis during the audit process. This enables your firm to compare non-identifiable data across clients over the previous ten years. Although client data may deviate from industry-wide data (i.e., clients may be somewhat larger or smaller than the industry average), the level of detail provided in the broad historical data allows for more sophisticated analysis to be performed, and thus more effective identification of unusual activity. Your firm's Central Data Analytics Group is increasingly being used to analyze client data during the fraud risk assessment phase of the firm's audits. Note that:

- The Central Data Analytics Group is capable of analyzing various types of data using data analytical models to identify audit relevant information.
- The general consensus in your firm is that the Central Data Analytics Group is very skilled at data analysis. As the Central Data Analytics Group does not employ any CPAs or anyone with an accounting background, their accounting knowledge is very limited. At times, the Central Data Analytics Group performs very innovative analyses, however, the audit relevancy of the information is not always apparent to the audit team. When this occurs, your firm's policy is to document why this information is not being used.
- When presenting the results of data analysis, the Central Data Analytics Group typically states the risk of a misstatement and the estimated dollar amount of misstatement. Your colleagues have reported that both of these numbers come over as very precise, yet the numbers are not always as reliable as information identified by traditional analytical procedures. At times, the actual misstatement has been found to be substantially higher than the estimate provided by the Central Data Analytics Group. Alternatively, there were times when no misstatement was identified.

In the case of the 2017 Madison audit, the Central Data Analytics Group is facilitating your fraud risk assessment of revenue by using **(predictive/ anomaly) analytical models** to analyze (***financial / non-financial***) information, specifically (***journal entries / e-mails***). The Central Data Analytics Group is experienced at using **(predictive/anomaly) models** to analyze (***financial / non-financial***) information such as (***journal entries / e-mails***). (**Predictive models** identify patterns in current data similar to patterns associated with previously identified issues/occurrences / **Anomaly models** identify statistical outliers indicating very high or low amounts based on you firm's client base). The Central Data Analytics Group identifies all activity that is deemed unusual regardless of the likely source of the activity (for example, error or fraud). The use of (**predictive/anomaly) models** to analyze (**journal entries / e-mails**) is discussed in more detail on the next page.

(1a) When using **(predictive/anomaly) models** to analyze **journal entries (financial information)** for the Madison audit, the Central Data Analytics Group is capable of identifying **journal entries** that affect revenue. For the Madison audit, the Central Data Analytics Group used this **financial information** to identify the number of **journal entries** that include revenue and were made just below the performance materiality threshold. Although the Central Data Analytics Group has explained what criteria they use for "just below the performance materiality" for the **journal entries**, this explanation contained substantial statistical jargon and was not well understood by your audit team. Several of your colleagues have reported similar issues with explanations received from the Central Data Analytics Group. The Central Data Analytics Group *only* performed this analysis using (**predictive/anomaly) models** for **journal entries** that affect revenue.

(1b) When using (**predictive/anomaly) models** to analyze **e-mails (non-financial information)** for the Madison audit, the Central Data Analytics Group is capable of identifying sentences in the **e-mails** that discuss revenue. For the Madison audit, the Central Data Analytics Group used this **non-financial information** to identify optimistic language used in internal and external **e-mails** for sentences that discuss revenue. Although the Central Data Analytics Group has explained what criteria they use for "optimistic language" in the **e-mails**, this explanation contained substantial statistical jargon and was not well understood by your audit team. Several of your colleagues have reported similar issues with explanations received from the Central Data Analytics Group. The Central Data Analytics Group *only* performed this analysis using (**predictive/anomaly) models** for sentences in **e-mails** that discuss revenue.

(2a) The Central Data Analytics Group employs **predictive analytical models** to identify patterns that are similar to previously identified issues. **Predictive models** rely on prior historical data to identify patterns and predict future events. **Predictive models** compare information in the data collected from clients associated with previously identified events/occurrences to current information. **Predictive models** may be used in the audit process to identify a pattern over several years associated with a previously identified material misstatement that may be indicative of a current material misstatement. For the current year Madison audit, the Central Data Analytics Group used **predictive models** to analyze the ratio of (*the number of* ***journal entries*** *affecting revenue just below performance materiality to the number of total* ***journal entries (financial information)*** */ the amount of optimistic language in external* ***e-mails*** *compared to internal* ***e-mails*** *for sentences that discuss revenue* ***(non-financial information)***) to data collected from all of your firms' manufacturing clients from previous years.

(2b) The Central Data Analytics Group employs **anomaly analytical models** to identify statistical outliers. **Anomaly models** rely only on current year (non-historical) data to identify statistical outliers. **Anomaly models** compare information in the data collected from your firm's client base to identify very high or low amounts or ratios. **Anomaly models** may be used in the audit process to identify very high or low ratios (i.e. gross margin, debt to equity, current ratio) that may be indicative of a current material misstatement. For the current year Madison audit, the Central Data Analytics Group used **anomaly models** to analyze the ratio of (*the number of*

journal entries *affecting revenue just below performance materiality to the number of total* ***journal entries (financial information)*** */ the amount of optimistic language in external* ***e-mails*** *compared to internal* ***e-mails*** *for sentences that discuss revenue* ***(non-financial information)***) to data collected from all of your firms' manufacturing clients in the current year.

(3 – this is shown in all conditions)
The Central Data Analytics Group informs you that after using (***predictive analytical models / anomaly analytical models***) (as discussed above) as part of Madison Inc.'s fraud risk assessment, the (***journal entries / e-mails***) were identified as containing unusual activity. This unusual activity may indicate that sales are overstated, and thus, may represent a heightened fraud risk. Alternatively, the Central Data Analytics Group may have identified unusual activity attributable to innovative or unusual manufacturing practices. Thus, the unusual activity identified may represent a significant fraud risk or have a reasonable explanation.

Despite the Central Data Analytics Group's ability to analyze (***journal entries / e-mails***) using **(predictive / anomaly) analytical models**, the Central Data Analytics Group does not have a strong understanding of accounting and auditing. Nonetheless, the Central Data Analytics Group stated that by using (***predictive analytical models / anomaly analytical models***) to analyze (***journal entries / e-mails***), they believe there is a 56% risk that revenue is overstated by some amount between \$270,000 and \$310,000. In the past your colleagues have reported that these estimates are often not accurate. At times the actual misstatement has been substantially higher than the estimate provided by the Central Data Analytics Group, whereas other times no misstatement was actually identified. Performance materiality for the 2017 Madison audit has been calculated as \$304,000.

Given the information provided from the Central Data Analytics Group, how would you assess fraud risk in the current year?

Very Low Fraud Risk	Low Fraud Risk	Slightly Low Fraud Risk	Medium Fraud Risk	Slightly High Fraud Risk	High Fraud Risk	Very High Fraud Risk

Assume 30 hours were initially budgeted to audit revenue. How would you adjust the budgeted hours for the revenue account in percentages (every 5% change results in a change of 1.5 hours)?

_________%

1) To what extent do you agree/disagree with the statement “the information presented from the Central Data Analytics Group represents a fraud risk”?

Strongly disagree	Moderately disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Moderatel y agree	Strongly agree

2) To what extent do you agree/disagree with the statement “I am confident in the accuracy of the information presented from the Central Data Analytics Group”?

Strongly disagree	Moderately disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Moderatel y agree	Strongly agree

3) Would you prefer to evaluate fraud risk WITHOUT the information presented from the Central Data Analytics Group?

Strongly prefer with the information	Moderately prefer with the informatio n	Slightly prefer with the informatio n	No preferenc e	Slightly prefer without the informatio n	Moderatel y prefer without the informatio n	Strongly prefer without the informatio n

4) Do you agree with incorporating the information identified by the Central Data Analytics Group into Madison’s fraud risk assessment?

Strongly disagree	Moderately disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Moderatel y agree	Strongly agree

5) How likely are you to rely on the information from the Central Data Analytics Group while performing your fraud risk assessment of Madison?

Very unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderatel y likely	Very likely

Please answer the following questions:

1) In the case you read, what type of information did the Data Analytics Group Analyze?
Financial information (journal entries just below materiality) ☐
Non-financial information (optimistic language in e-mails) ☐

2) In the case you read, what type of data analytical model did the Data Analytics Group utilize?
Anomaly models that identify statistical outliers (such as very high or low ratios compared to industry averages from the firm's client base) ☐
Predictive models that identify patterns (for example of ratios) similar to patterns associated with previously identified issues/occurrences ☐

3) Age _______

4) Gender
Male ☐
Female ☐

5) Years of Professional accounting experience ___________

6) Years of Audit experience _____________

7) What percent of your annual chargeable hours are typically assigned to manufacturing clients?__________________

8) What percent of your annual chargeable hours are typically assigned to privately held clients?_________________

9) What is your highest degree of education earned?
High School ☐
Some College ☐
Associate degree ☐
Undergraduate ☐
Some graduate ☐
Master degree ☐
Doctoral degree ☐

10) What best describes the firm you work for?
Local ☐
Regional ☐
National ☐
International ☐

11) What is your position/rank (or equivalent title)?
Staff ☐

Senior ☐
Supervisor ☐
Manager ☐
Director ☐
Partner ☐
Other (Please specify) ____________________

12) Are you a CPA?
Yes ☐
No ☐

13) Please list any other relevant certifications _________________________

14) How experienced are you in discussing fraud risk during brainstorming sessions?

Not at all experienced	Slightly experienced	Moderately experienced	Very experienced	Extremely experienced

15) How experienced are you in adjusting the budget in response to a fraud risk identified during a brainstorming session?

Not at all experienced	Slightly experienced	Moderately experienced	Very experienced	Extremely experienced

16) Do you have experience using data analytics in the audit process?
Yes ☐
No ☐

17a) If you answered yes to #16, How experienced are you in using data analytics that identify statistical outliers such as unusually high/low fluctuations or ratios (anomaly models) as part of your job function?

Not at all experienced	Slightly experienced	Moderately experienced	Very experienced	Extremely experienced

17b) If you answered yes to #16, How experienced are you in using data analytics that compare current data against previously identified issues/occurrences to identify similarities (predictive models) as part of your job function?

Not at all experienced	Slightly experienced	Moderately experienced	Very experienced	Extremely experienced

18) How experienced are you in using financial data as part of your job function?

Not at all experienced	Slightly experienced	Moderately experienced	Very experienced	Extremely experienced

19) How experienced are you in using nonfinancial data as part of your job function?

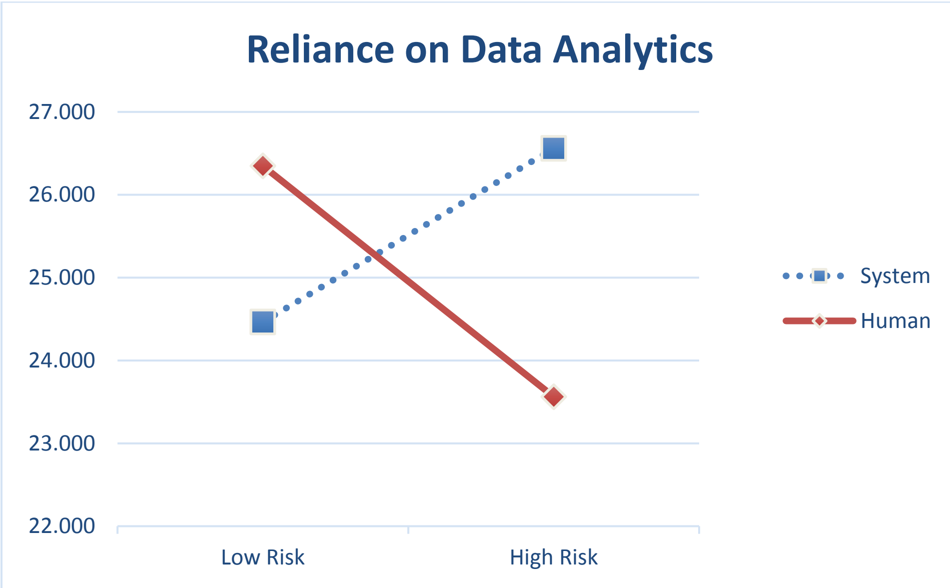
Not at all experienced	Slightly experienced	Moderately experienced	Very experienced	Extremely experienced

20) How do you believe a supervisor would have evaluated your decisions if no fraud was identified in the revenue cycle?

Below expectations	Slightly below expectations	Met expectations	Slightly above expectations	Above expectations

APPENDIX E: STUDY 3 FIGURES

Panel A



Panel B

Figure 4- Graphical depiction of results of study 3

APPENDIX F: STUDY 3 TABLES

Table 6 – Demographic profile of study 3 participants (n=92)

Panel A

		n	%
Gender		n	%
	Male	51	55.4%
	Female	41	44.6%
Title			
	Staff	27	29.3%
	Senior	18	19.6%
	Supervisor	5	5.4%
	Manager	28	30.4%
	Director	14	15.2%
Size			
	Local	24	26.1%
	Regional	29	31.5%
	National	10	10.9%
	International	29	31.5%

Panel B

		GENDER System n	%	Human n	%
High Risk	Male	18	72.0%	6	37.5%
	Female	7	28.0%	10	62.5%
Low Risk	Male	17	60.7%	10	43.5%
	Female	11	39.3%	13	56.5%

		TITLE System n	%	Human n	%
High Risk	Staff	8	32.0%	5	31.3%
	Senior	3	12.0%	4	25.0%
	Supervisor	1	4.0%	3	18.8%
	Manager	10	40.0%	3	18.8%
	Director	3	12.0%	1	6.3%
Low Risk	Staff	6	21.4%	8	34.8%
	Senior	6	21.4%	5	21.7%
	Supervisor	1	3.6%	0	0.0%
	Manager	11	39.3%	4	17.4%
	Director	4	14.3%	6	26.1%

		FIRM SIZE System n	%	Human n	%
High Risk	Local	10	40.0%	2	12.5%
	Regional	5	20.0%	7	43.8%
	National	2	8.0%	2	12.5%
	International	8	32.0%	5	31.3%
Low Risk	Local	6	21.4%	6	26.1%
	Regional	8	28.6%	9	39.1%
	National	3	10.7%	3	13.0%
	International	11	39.3%	5	21.7%

Table 7 - Results of study 3 Reliance variable

Panel A - Descriptive Statistics - Reliance mean [standard deviation]

	Presentation Source		
Control Risk Level	**System**	**Human**	
High Risk	**26.560**	**23.563**	**25.390**
	[5.598]	**[6.572]**	**[6.099]**
	n=25	**n=16**	**n=41**
Low Risk	**24.464**	**26.348**	**25.314**
	[5.935]	**[4.488]**	**[5.365]**
	n=28	**n=23**	**n=51**
	25.453	**25.205**	
	[5.820]	**[5.535]**	
	n=53	**n=39**	

Panel B: ANCOVA Results

Source of variation	df	MSE	F-Statistic	p-value
Presentation Source[a]	**1**	**12.723**	**0.41**	**0.523**
Control Risk Level[b]	**1**	**3.832**	**0.12**	**0.726**
Presentation Source * Control Risk Level	**1**	**120.697**	**3.90**	**0.052**
Age	**1**	**98.910**	**3.19**	**0.078**
Error	**87**	**30.981**		

The dependent variable is measured using the Reliance scale adapted from Hampton (2005). The reliance dependent variable is the total score of five questions answered on 7 point likert scales. The Reliance measure consists of four questions adapted from the Hampton (2005) scale and one question measuring trust. These questions measure participants 1) agreement with the information identified by the data analytics, 2) confidence in the accuracy of the findings of the data analytics, 3) willingness to incorporate the findings from the analytics into their decision making, 4) willingness to rely on the findings of the data analytics, 5) trust in the data analytics. The total Reliance score may range from 5 to 35. The means are reported in Panel A.

[a]"Presentation Source" was manipulated by informing participants that the source presenting the results of the data analytics was a Self-generating System (Presentation Source=0) or a Data Scientist (Presentation Source=1)

[b]"Control Risk Level" was manipulated by varying whether the data analytics presented a low risk of misstatement (Control Risk Level=0) or a high risk of misstatement (Control Risk Level=1)

Table 8 – Results of study 3 likelihood that fraud has occurred variable

Panel A - Descriptive Statistics - Likelihood of Fraud mean [standard deviation]

	Presentation Source		
Control Risk Level	**System**	**Human**	
High Risk	**4.440** **[1.502]** **n=25**	**4.188** **[1.2234]** **n=16**	**4.341** **[1.389]** **n=41**
Low Risk	**3.536** **[1.575]** **n=28**	**4.348** **[1.748]** **n=23**	**3.902** **[1.688]** **n=51**
	3.962 **[1.593]** **n=53**	**4.282** **[1.538]** **n=39**	

Panel B: ANCOVA Results

Source of variation	df	MSE	F-Statistic	p-value
Presentation Source[a]	**1**	**3.333**	**1.52**	**0.221**
Control Risk Level[b]	**1**	**2.720**	**1.24**	**0.268**
Presentation Source*Control Risk Level	**1**	**4.246**	**1.94**	**0.168**
Data Analytics Experience[c]	**1**	**20.029**	**9.14**	**0.003**
Error	**87**	**2.193**		

Panel C: Planned Comparison Test

Source of variation	F value	p-value
System/LowRisk < All Other Conditions	**5.01**	**0.028**

The dependent variable is participants assessment of the likelihood that fraud has occurred on a 7 point likert scale

[a]"Presentation Source" was manipulated by informing participants that the source presenting the results of the data analytics was a Self-generating System (Presentation Source=0) or a Data Scientist (Presentation Source=1)

[b]"Control Risk Level" was manipulated by varying whether the data analytics presented a low risk of misstatement (Control Risk Level=0) or a high risk of misstatement (Control Risk Level=1)

[c]Data Aanalytics Experience measures participants experience using data analytics as part of the audit process on a 7 point likert scale

APPENDIX G: STUDY 3 EXPERIMENTAL MATERIALS

CONSENT PAGE ON QUALTRICS:

You are invited to take part in a research study conducted by Jared Koreff, PhD candidate in the Kenneth G. Dixon School of Accounting at the University of Central Florida. The only requirement to participate is that you are currently employed as an external financial statement auditor and have experience assessing control risk. Please read the following case carefully, as you will be asked a series of questions about the case related to the findings of data analytics.

To thank you for your time, at the completion of the survey you can choose between receiving a $10 amazon gift card or having the researcher make a donation to a charity on your behalf.

Whether you take part is up to you. If you decide to participate in this project please understand that your participation is voluntary and that you have the right to withdraw your consent or discontinue participation at any time without penalty. Refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled.

If you would like to know the results of the study please e-mail the primary researcher: Jared.Koreff@ucf.edu.

You must be 18 years of age or older to take part in this research study.

If you have questions, concerns, or complaints, please contact Jared Koreff, Graduate Student, Kenneth G. Dixon School of Accounting, College of Business Administration at (407) 823-2957 or Jared.Koreff@ucf.edu or Dr. Vicky Arnold, Faculty Supervisor, College of Business Administration at (407) 823-3192 or Vicky.Arnold@ucf.edu.

To contact IRB about your rights in the study or to report a complaint: Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been reviewed and approved by the IRB. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901

CLIENT INFORMATION
Assume this is your third year on the audit team conducting the audit of Omega Computer Parts ("Omega"), and you are the in-charge on the job. Omega is publicly traded and has been a client for 10 years.

Omega is one of the leading manufacturing companies in the United States and has operations in all fifty states. Omega manufactures computer hardware and peripheral equipment that are primarily sold to small and medium sized businesses. Omega has a highly qualified and experienced accounting department. Omega devotes substantial resources to recruit, train and retain qualified accountants. Your firm has established a good working relationship with Omega's management over the past 10 years. Omega's management usually accepts audit findings; however, at times there is substantial discussion of proposed audit adjustments. These discussions are professional and an amicable agreement has always been reached.

DATA ANALYTICS PILOT PROGRAM:
During the current year, upper level management of your firm has initiated a pilot program to utilize data analytics on a sample of low-risk audit clients. Although the pilot program thus far has identified several ineffective uses and opportunities for improvement in the use of data analytics, your colleagues have reported the findings of data analytics can be effective at identifying audit relevant information.

The Omega audit has been selected to be part of this data analytics pilot program as Omega has historically been a low risk client. The control risk of Accounts Payable (AP) for Omega has always been "low". Thus, data analytics will be used to aid in the control risk assessment of AP for the Omega audit.

TASK OBJECTIVE
Based on the information provided in this case, you will be asked to make a series of decisions based on the findings of data analytics presented to you. You will be asked how likely you are to increase control risk and the likelihood that fraud has occurred in the AP business process. Finally, you will be asked your willingness to rely on the information identified from the data analytics. PLEASE READ THE FOLLOWING INFORMATION VERY CAREFULLY.

CURRENT YEAR AUDIT INFORMATION

Your firm has provided several training sessions and created memos informing clients how to create and format financial and nonfinancial data using the AICPA's proposed Audit Data Standards. After receiving these data, your firm utilizes data analytics to identify and analyze audit relevant information. For the Omega audit, data analytics are *only* applied to the AP data for the current year audit.

Omega's AP process follows a fairly standard business process. The sequence to write checks is as follows: (1) create a purchase order, (2) sign a purchase order, (3) release a purchase order, (4) receive goods, (5) receive invoice, and (6) pay invoice.

After receiving the data from Omega, you [*utilized your firm's internal data analytic software on your computer / contacted your firm's internal data scientist who utilized data analytics*] to analyze the AP data provided. Specifically, the [*software / data scientist*] uses pre-programmed data analytics to evaluate all records related to AP and assess control risk. Subsequent to [*uploading the AP data into the software on your computer and clicking "run" / e-mailing the AP data to your firm's data scientist and asking them to analyze the data*], pre-programmed data analytics were performed and the results were provided to you.

While violations in the AP business process identified by the data analytics may be indicative of internal control issues (e.g., an AP clerk writing duplicate checks to vendors), such violations may also have justifiable explanations (e.g., a change to a purchase order results in requesting new approvals, which impacts the second and third step). Thus, violations may be indicative of a misstatement or fraud, or may justifiably deviate from designed processes.

After analyzing the AP business process using the data analytics discussed above, the [*report displayed by the software on your computer / report handed to you by the data scientist*] indicated that the proportion of checks written in relation to invoices received was very *[high / low]*, which represents a *[heightened / minimal]* risk of a material misstatement.

The report of the findings of the data analytics provided by the [*software / data scientist*] indicating a *[heightened / minimal]* risk of misstatement is presented on the next page.

Omega Computer Parts
Data Analytics Report on AP Process
As of December 14, 2017

Client number 000125876 **Time** 3:41 PM

Data analytics identified a very [*high / low*] number of checks written as a percentage of invoices received.

As shown in the chart below, the ratio of "Payment" to "Invoice Received" (31,817 to 29,255) is very *[high / low]*.

Note: "Frequency" refers to the number of times an "Activity" occurs. Thus, while a single shipment may consist of multiple goods, the Frequency of "Goods Received" would count as 1.

Activity	Frequency	Frequency of Activity / Frequency of "Create Purchase Order"
Create Purchase Order	26,185	1.0000
Sign Purchase Order	25,648	0.9795
Release Purchase Order	28,748	1.0979
Goods Received	24,724	0.9442
Invoice Received	29,255	1.1172
Payment	31,817	1.2151

Data analytics assess the risk of material misstatement as [LOW / HIGH].

The results of the data analytics are based on raw data analysis and do not incorporate financial statement audit knowledge.

The findings from the [*software / data scientist*] using data analytics present evidence of a *[high / low]* risk of misstatement. Your colleagues have reported that information provided by the [*software / data scientist*] results in changing audit procedures about half of the time. When audit procedures are not being changed, your firm's policy is to document why data analytic information is not being used. Your colleagues have reported that documenting why the data analytics are not being used is generally accepted within your firm, and this documentation takes minimal time compared to changing audit procedures.

After viewing the results of the data analytics suggesting a [*high / low*] risk of misstatement, you performed an initial inquiry with Omega's Director of AP. The Director of AP stated that at times more than one check is written for an invoice due to favorable payment terms. The Director of AP proceeded to explain that at times, vendors will allow for a discount on the total invoice amount, if a portion of the invoice is paid within 15 days of the invoice date; however the Director is uncertain how frequently this occurs.

1) Based on the information provided by the data analytics, how likely are you to increase the level of control risk assigned to Accounts Payable above “low”?

Extremely unlikely	**Moderately unlikely**	**Slightly unlikely**	**Neither likely nor unlikely**	**Slightly likely**	**Moderately likely**	**Extremely likely**

2) Based on the information provided by the data analytics, what do you believe is the likelihood that fraud has occurred in the Accounts Payable process?

Extremely unlikely	**Moderately unlikely**	**Slightly unlikely**	**Neither likely nor unlikely**	**Slightly likely**	**Moderately likely**	**Extremely likely**

3) To what extent do you agree/disagree with the findings of the data analytics?

Strongly disagree	Moderately disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Moderatel y agree	Strongly agree

4) To what extent do you agree/disagree with the statement: “I am confident in the accuracy of the findings of the data analytics”?

Strongly disagree	Moderately disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Moderatel y agree	Strongly agree

5) Would you prefer to make audit decisions WITHOUT the additional information obtained from the data analytics?

Strongly prefer with the information	Moderately prefer with the informatio n	Slightly prefer with the informatio n	No preferenc e	Slightly prefer without the informatio n	Moderatel y prefer without the informatio n	Strongly prefer without the informatio n

6) Do you agree with incorporating the findings of the data analytics into your audit decisions?

Strongly disagree	Moderately disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Moderate ly agree	Strongly agree

7) How likely are you to rely on the findings of the data analytics?

Very unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderatel y likely	Very likely

Please answer the following questions:

1) How were the findings of the data analytics communicated to you?
- A human (your firm's internal data scientist) handed you a report ☐
- A report displayed on your computer by the data analysis software ☐

2) Data analytics identified the risk of misstatement of AP as:
- Low risk ☐
- High risk ☐

3) Age _______

4) Gender
- Male ☐
- Female ☐

5) Years of Professional accounting experience ___________

6) Years of Audit experience _____________

7) What is your highest degree of education earned?
- High School ☐
- Some college ☐
- Associates degree ☐
- Undergraduate ☐
- Some graduate ☐
- Master degree ☐
- Doctoral degree ☐

8) What best describes the accounting firm you work for?
- Local ☐
- Regional ☐
- National ☐
- International ☐

9) What is your position/rank?
- Staff ☐
- Senior ☐
- Supervisor ☐
- Manager ☐
- Director ☐
- Partner ☐
- Other (please specify) ____________

10) Are you a CPA?

Yes ☐
No ☐

11) Please list any other relevant certifications ______________

12) How experienced are you in using data analytics as part of the audit process?

Not at all experienced	Slightly experienced	Somewhat experienced	Very experienced	Extremely experienced

13) How experienced is your organization at using data analytics as part of the audit process?

Not at all experienced	Slightly experienced	Somewhat experienced	Very experienced	Extremely experienced

14) How experienced are you at auditing accounts payable?

Not at all experienced	Slightly experienced	Somewhat experienced	Very experienced	Extremely experienced

15) In the case you read, what is your level of trust in the findings of the data analytics?

Very low	Moderatel y low	Slightly low	Neither high nor low	Slightly high	Moderatel y high	Very high

16) What is your level of self-confidence in performing the data analytics used in this case on your own ?

Very low	Moderately low	Slightly low	Neither high nor low	Slightly high	Moderatel y high	Very high

17) How do you believe a supervisor would have evaluated your decisions if no misstatement, error nor fraud, was identified in the AP process?

Below expectations	Slightly below expectations	Met expectations	Slightly above expectations	Above expectations

APPENDIX H: IRB APPROVALS

University of Central Florida

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Jared Koreff** and Co-PI: **Steven Gale Sutton**

Date: **December 09, 2014**

Dear Researcher:

On 12/09/2014, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review:	Exempt Determination
Project Title:	What makes panopticism effective? Evidence from the healthcare industry
Investigator:	Jared Koreff
IRB Number:	SBE-14-10792
Funding Agency:	
Grant Title:	
Research ID:	N/A

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Kanielle Chap

IRB Coordinator

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Jared Koreff**

Date: **November 17, 2016**

Dear Researcher:

On 11/17/2016, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review:	Exempt Determination
Project Title:	The Impact of Data Analytics on Auditors' decisions
Investigator:	Jared Koreff
IRB Number:	SBE-16-12728
Funding Agency:	
Grant Title:	
Research ID:	N/A

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Patria Davis on 11/17/2016 07:45:37 AM EST

IRB Coordinator

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Jared Koreff**

Date: **March 13, 2017**

Dear Researcher:

On 03/13/2017, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review:	Exempt Determination
Project Title:	The Impact of a human factor on auditor's reliance on data analytics
Investigator:	Jared Koreff
IRB Number:	SBE-16-12849
Funding Agency:	
Grant Title:	
Research ID:	N/A

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Kamille Chap

Signature applied by Kamille Chaparro on 03/13/2017 11:30:24 AM EDT

IRB Coordinator