Data Analytics in Information Systems (IS) Auditing:

An Examination of the Cost-Effectiveness of the Use of Data Analytics in Information Systems Auditing

by

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ABSTRACT

The information systems audit process is a costly, repetitive, manual process entailing high labor costs. The central research question was how the use of data analytics in the information systems audit process can improve efficiency and minimize costs. This qualitative study explored the perceptions and experiences of IS auditors on factors affecting the wide use of data analytics in IS audit practice to minimize costs and improve audit process efficiency.

Positive social and enterprise changes may occur when IS audits are delivered efficiently at low cost.

Keywords: Data, Analytics, Labor, Cost, Efficiency, Audit, Information, Systems

DEDICATION

I dedicate this work to my family members for the support, sacrifices, patience, time, and motivation over many years of my pursuit of this dream. My parents, Tinos and Belita Manhanga raised five children in a low-income suburb called Glen-Norah in Harare, Zimbabwe. They preached the value of education to me despite never having attained any post-secondary education themselves. My father, Tinos, worked as an accounting clerk while my mother Belita did subsistence farming to supplement my father's income to support my early education. I am grateful to my siblings for all the emotional and moral support in my life.

Most importantly, I dedicate this work to my wife, Florence, whose unwavering support helped me navigate the challenges of being a full-time employed data scientist, doctoral student, husband, and parent. She spent a great deal of time alone with our two young boys as I pursued my PhD. She sacrificed her own education by postponing her graduate school enrollment so she could look after the kids while I complete my doctoral studies.

When I started my doctoral studies my son Leo was four years old and Liam was not even born. Today Leo is eight and Liam just turned three. They have not been able to understand why dad is always studying in his office. These two boys have been a major motivation for me as I navigate this challenging doctoral program.

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CHAPTER 1: INTRODUCTION

Information systems (IS) auditing has been an area of practice since the 1960s, termed at that time “management information systems” (Hirschheim & Klein, 2012). Audit and compliance practices trace their origins to accounting, where certain historical procedures were used to examine financial transactions during the 1800s (Teck-Heang & Ali, 2008). Today, advances in technology are providing new ways to conduct audits efficiently and cost-effectively.

According to Information Systems Audit and Control Association (ISACA) (2014a), the goals of IS audits are to provide continuous monitoring and reporting of any violations in the assurance of confidentiality, integrity, and availability of systems and data in an effective, efficient, secure, and reliable manner. The objectives include: evaluation of systems and processes that secure organizational data; ensuring IS processes comply with regulatory requirements, organizational policies and standards; determining inefficiencies in IS systems; identifying risks to an organization's IS assets; and identifying methods to mitigate those risks (Hall, 2015, p.14). Efforts to achieve these objectives are disrupted by a variety of challenges along the way.

There are a number of forces complicating the IS audit process. The main forces are the rapid growth of data across industries, the proliferation of devices linked to the internet of things (IoT), and regulations (Bhatt, Dey, & Ashour, 2017; Brown-Liburd, Issa, & Lombardi, 2015). Over the past decade, there has been a dramatic increase in the number of industrial devices connected to the internet with a corresponding increase in data to be collected, monitored, analyzed and stored (Chen, Mao, & Liu, 2014; Sun, Song, Jara, & Bie, 2016). Management of these Industrial IoT devices negatively impacts audit efficiency and increases costs (Dai & Vasarhelyi, 2016; Pasquier et al., 2018).

A rapid adoption of advanced technologies in business has given rise to computer-aided audit and compliance tools. The concept of automated monitoring and control is being applied in IS auditing to curb labor costs (Byrnes et al., 2018). In spite of this early adoption of computer-aided audits, data analytics is not yet well- embraced in the practice (Hampton & Stratopoulos, 2016). According to Hampton and Stratopoulos (2016), most teams using computer-aided auditing rely on basic Excel spreadsheets for capturing data for analysis. They also claimed Excel spreadsheets are the most popular data analytics tool on most projects.

In a recent issue of the Information Systems Audit and Control Association Journal (ISACA), Cooke (2018) listed data analytics as one of the top ten emerging technologies most likely to deliver significant value to the IS audit practice. Data analytics in this study refers to the process of extracting, analyzing, and visualizing patterns that inform and guide audit assurance (Tsai, Lai, Chao, & Vasilakos, 2015). It can be used to enhance audit process efficiency at lower costs. This study sought to provide a new understanding of the operational effectiveness that can be obtained by using data analytics. This will enable the industry to cost-efficiently leverage new technology to enforce growing compliance regulatory requirements.

Background of Study

According to Hux (2017) the current audit education curriculum does not include data analytics, increasing the need for IS auditors to engage costly specialists on projects. Some recent research is questioning if the auditor is still the most appropriate person to provide the assurance service, considering the skill gap and outdated audit frameworks (Bauer & Estep, 2017). In a related study, Tysiac (2015) suggested that the future audit workforce will require specialized training in data analytics, and that auditing standards may need to be updated to reflect this impact.

In spite of the slow adoption of the broader use of data analytics in the practice, literature covering this field is replete with early research that studied the use of random statistical sampling (Ponemon & Wendell, 1995). Curtis and Payne (2008) discovered that computer-assisted audit techniques are under-utilized although research has proven this would improve the efficacy of audits in organizations of all sizes. A thorough examination of the current data environment and social media activities requires continuous client monitoring through data analytics (Bumgarner & Vasarhelyi, 2018). Continuous auditing involves automation of these tasks to provide ongoing assurance through the identification and mitigation of operational risks (Ruiter, 2017). The resulting recommendations can influence management decision-making for both tactical and strategic purposes (Sun & Vasarhelyi, 2017). Some of the recommendations included the use of internet of things (IoT) devices.

The broad adoption of the internet of things (IoT) adds complication to the IS auditing practice, since it is difficult to monitor and analyze data coming from all connected devices using current practices (Cooke, 2018). IoT is a collection of interconnected devices and services that capture and transmit data to manage infrastructure services (Alkhalil & Ramadan, 2017). The fact that these systems generate data which travel across unmonitored perimeters creates obstacles to compliance with SAS No. 56 (Elkhodr, Alsinglawi, & Alshehri, 2018). SAS No.56 provides guidance on the use of analytical procedures; enforces its use in planning; and directs the review of all audit stages (Plumlee, Rixom, & Rosman, 2015). Analytical procedures include simple to complex comparisons of data elements relationships and substantive tests conducted to obtain audit evidence (Westland, 2017). The transmission of data across networks creates data provenance ramifications and complicates privacy and security considerations for IS auditors (Alkhalil & Ramadan, 2017). There are also assurance predicaments associated with the old audit standards and frameworks which are not adaptable to IoT requirements (Raphael, 2017). All these IoT challenges broaden the landscape, impacting efficiency and increasing costs (Duncan, Whittington, & Chang, 2017).

The accelerated adoption of the IoT across industry is encouraging implementation of big data technologies to store and analyze large datasets (Giles, 2019). The emergence of big data has compounded the efficiency and cost containment issues of the IS audit process (Dzuranin & Mălăescu, 2016; Zhang, Yang, & Appelbaum, 2015). Big data is defined as massive volumes of rapidly created, structured and unstructured data which can be used to enhance insights and decision-making (Song & Zhu, 2016, p. 365). According to Gepp, Linnenluecke, O'Neill, and Smith (2018), big data techniques can be a great complement to the audit practice, but their research determined the auditing field is lagging behind with regard to the adoption of these new techniques. Beyond technological advances, the expansion of the regulatory landscape is adding another set of predicaments to the practice (Martin, Sanders, & Scalan, 2014).

The Congress of the United States of America passed the Sarbanes-Oxley Act, (SOX), in 2002. SOX introduced changes to the financial practice and corporate governance regulations by emphasizing management assessment of internal controls with section 404 focused on IT internal controls. This law is considered to be one of the costliest regulations in the history of the audit practice (Kokash, 2014). SOX enforcement impacts the IS audit process' effectiveness, efficiency, and labor costs (Willits & Nicholls, 2014).

Countries around the world are also introducing new laws for handling customer and personal data. Examples of some recent laws that impact labor costs and process efficiency are Europe's General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA) (Banakar, Shah, Shastri, & Chidambaram, 2019, Goldman, 2019). The GDPR was enacted by the European Union to require businesses to protect personal data of customers who are citizens of EU member countries (Diker Vanberg& Ünver, 2017). In United States, the State of California drafted the CCPA, which takes effect in 2020, to regulate how businesses handle the personal information of California consumers (Harding, Vanto, Clark, Hannah Ji, & Ainsworth, 2019). The assurance industry is slow in leveraging new data analytics tools and techniques to comply with these new legislations (Barr-Pulliam, Brown-Liburd, & Sanderson, 2017).

There are three types of data analytics: descriptive, predictive, and prescriptive (Dinesh Kumar & Ramanathan, 2017). According to Davenport (2013), descriptive analytics is the use of basic statistical techniques to show relationships in data from which to formulate hypotheses. Predictive analytics offers insights into the future of a phenomenon of interest using the inferences from descriptive analytics. Prescriptive analytics is the development of a solution to anticipated shortcomings of a phenomenon. All these could be used in the IS audit process to describe anomalies in enterprise systems and data, proactively provide alerts on impending risks, and minimize business costs (Earley, 2015; Vashisht & Gupta, 2015).

A new data analytics technique common across descriptive, predictive, and prescriptive analytics is text analysis, sometimes referred to as natural language processing (NLP). Text analysis in this study refers to the process of extracting and analyzing plain text data or unstructured data to find patterns that inform and guide audit assurance for better corporate decision-making (Miner, Elder IV, & Hill, 2012, p.29). This new technique, made possible by advances in computing power, has the potential to improve fraud detection (Müller et al., 2016). Kuenkaikaew (2013) explored the benefits of using predictive auditing with text analysis and proposed a predictive audit framework as a step toward developing continuous monitoring to improve the cost-effectiveness of the processes.

Audit data analytics (ADA) is a data science technique applied to generate new forms of evidence difficult to achieve using older methods (Hoogduin, Yoon, & Zhang, 2014). One complication to using IT in the IS audit process has been to inject incremental improvements to increase the efficiency of the process without creating new gaps (Issa, 2013). Technologies like ADA could be used to transform the entire system (Sun & Vasarhelyi, 2017). It could enable continuous assurance by providing early alerts to potential problems, spreading monitoring across periods, and enabling remote audits to reduce costs (Cao, Chychyla, & Stewart, 2015). These techniques have the potential to improve fraud detection and reduce false positives (Issa, 2013). The problem statement explores factors impacting the IS audit process' costs and efficiency.

Problem Statement

The general problem addressed in this study was that IS audits are not being completed in a timely and cost-effective manner to meet regulatory requirements (Oussii & Boulila Taktak, 2018). The IS audit process is a costly, repetitive, manual process that entails high labor costs (Issa, Sun, & Vasarhelyi, 2016). The audit practice has responded to issues of inefficiency by promoting industry-focused specialist engagements (Cahan, Godfrey, Hamilton, & Jeter, 2008). The fact that the audit profession is increasingly relying on many specialist roles, such as data analysts, data scientists, and machine learning specialists, to deliver a complete project, attests to the growing problem of project cost increases (Bills, Jeter, & Stein, 2014; Cahan, Jeter, & Naiker, 2011).

Cahan, Jeter, and Naiker (2011) investigated specialist auditor (i.e., auditors who have data analytics expertise) pricing and quality and concluded that clients engage specialists at a premium fee for the presumed quality. Client bargaining power on specialists' fees is low if a firm has to outsource IS auditing (Bills et al., 2014). Some organizations have been offshoring portions of their IS audit requirements to reduce fees. The emergence of automated controls that fully comply with regulatory requirements without manual intervention could transform the audit process and decrease costs (Shaikh et al., 2018).

The steady increase in regulatory requirements from government and industry is putting more pressure on the IS audit practice to automate routine tasks. Repetitive tasks seem to multiply with each new regulation, hampering efforts to contain labor costs (Dey & Lim, 2018). For example, research on Nike Corporation's supplier monitoring regulatory strategy concluded that an increase in regulations directly increases labor costs

(Locke, Qin, & Brause, 2007). Penalties and fines for regulatory non-compliance are significant costs levied on organizations failing to provide full assurance (Cart, 2014). Reputation risk and increasing business cost arising from the labor-intensive manual activities of IS audit could further expand labor budget (Adams, 2008).

In a related study, Oldhouser (2016) claimed the complexity and repeatability of audit work tasks are further complications that drag the audit practice behind in the adoption of new technologies. Although technology has re-engineered business processes, the audit practice has continued to use decades-old practices that are no longer effective (Mahzan & Lymer, 2014). Curtis and Payne (2014) concluded that fear of the unkown is holding back the audit community from adopting newer technologies that can improve efficiency and effectiveness.

Another impediment to transforming the IS audit practice is that old standards have not been updated and newer technologies appear to contravene existing auditing standards (Titera, 2013). Current audit practice standards and guidelines should be reviewed and adjusted to remove barriers to the effective use of advanced technologies such as data analytics (Titera, 2013). Richins, Stapleton, Stratopoulos, and Wong (2017) proposed that educators, standard setters, and professional bodies must embrace big data analytics as a new way of delivering audit evidence. They claim structured data has always been the primary input in the audit process; therefore, the emergence of new forms of data should not impede advances in the practice.

LaValle, Lesser, Shockley, Hopkins, and Kruschwitz (2011) claimed data is not the biggest obstacle to gaining competitive advantages; the real limiting factors are accessibility and availability of the right analytic techniques to aid decision-making.

Some of the critical techniques that fall under descriptive, predictive, and prescriptive analytics include basic data analysis, text analysis, machine learning, deep learning, simulation and optimization. Data analytics could offer powerful tools to the field of IS Audit (Gambetta, García-Benau, & Zorio-Grima, 2016; Najafabadi et al., 2015; Vashisht & Gupta, 2015). The use of open-source analytics tools like Python, R, and Scala could also accelerate the transformation (Davenport & Patil, 2012; Muenchen, 2014). Given that Müller et al. (2016) found that 80% of enterprise data is no longer structured, advanced analytics tools and techniques like these open-source tools could help make IS audit completeness a reality. Data analytics is now one of the critical levers of competitive advantage for data-driven organizations (Sun & Vasarhelyi, 2017). A study on the application of big data in econometrics by Varian (2014) concluded that the use of advanced data analysis methods improves business performance. In a related study Chen, Preston and Swink (2015) concluded organizational-level big data analytics use has direct positive influence on value creation.

Purpose of the Study

The purpose of this study is to understand how the use of data analytics in the IS audit process can lower labor costs. A survey of industry literature demonstrated numerous accounting publications that explored the value of data analytics in business, but none has yet explicitly focused on their impact on IS audit processes. This study will provide a new understanding of the potential operational benefits of using data analytics in IS audit practice.

This study achieved its stated goal by surveying professionals who are members of ISACA possessing ISACA certifications. The survey elicits perceptions and experiences of IS audit professionals regarding the use of data analytics in the practice. The study leveraged grounded theory to develop an approach grounded in the surveyed data to establish the stated goals. Data from a sample of 27 participants, all ISACA members with experience in IS audit and certified as audit professionals was analyzed. Of 33 responses received 27 were deemed usable. The sample size of 27 out of 33 participants in this study was enough to produce results that can be generalized across the IS audit fraternity. Qualitative research sample sizes should not be too large or too small (Yin, 2009, p.35). It may be challenging to synthesize large datasets and achieve analytical saturation qualitatively (Yin, 2009, p.35). The validity of the quality of the responses from participants was assumed to be high because ISACA is considered the leading institution of information system audit and control in the world (ISACA, 2014a; Tang, Norman, & Vendrzyk, 2017).

Significance of the Study

This study established the potential benefits of using data analytics in the IS audit process to improve efficacy and reduce labor costs. The results of this study provided valuable insights to senior management and audit leadership in the areas of reducing cost, improving efficiency, and decision-making. The findings of this study can be used to advance research focused on the IS audit practice by highlighting key gaps in existing frameworks.

The ability to efficiently audit and process 100 percent of enterprise data in a cost-effective manner makes research on the value of data analytics in IS audit process an appealing endeavor (Schneider, Dai, Janvrin, Ajayi, & Raschke, 2015). In addition, this study's focus on data analytic techniques could also help advance research on optimal audit sample sizes to improve process efficiency. The potential economies resulting from deploying data analytic techniques offer great promise in terms of cost reduction and reusability across many organizational units (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

Auditing firms and professionals have an opportunity to increase the value they bring to their clients through the use of data analytics (Appelbaum, Kogan, & Vasarhelyi, 2017). It can bring invisible anomalies to the surface and enable real-time resolution of violations in corporate environments, minimizing risks (Earley, 2015). These processes can help IS audit teams accomplish more tasks with fewer resources; thus it may provide more cost-effective recommendations (Stuart & Prawitt, 2011). Clients and internal assurance teams could benefit from the use of data analytics through automation of analysis, consistency, and accuracy (Stuart & Prawitt, 2011).

A recent study on the opportunities and challenges of data analytics in financial auditing by Earley (2015) concluded there is significant promise in improving audit quality through the use of analytics. According to Earley (2015) the possible benefits include being able to process and test large datasets; improved audit quality; enhanced anomaly detection; and solving more complicated problems. Accounting and financial audit teams can leverage data analytics as part of the strategy to enable continuous auditing, provide efficiency, reduce labor costs, and prevent fraud (Boritz, Hayes, & Lim, 2013). The audit practice in general could benefit from training in basic data analytics and its applicability (Cao, Duan, & Li, 2015).

Earley (2015) pointed out some significant obstacles that the practice may face in the effort to adopt data analytics. These were categorized into four broad areas as follows: training and experience of auditors; data availability; audit relevance and integrity; and expectations of the regulators and business users (Earley, 2015). There are many studies of the auditing profession, but due to the general perception that the IS audit is part of the accounting profession, there is little academic research on the IS audit profession itself (Curtis, Jenkins, Bedard, & Deis, 2009; Kim, Teo, Bhattacherjee, & Nam, 2017). This study will add to the body of research of the practice and findings will advance the IS audit practice by producing relevant research literature. Introducing basic data science into IS audit professional training or academic training could produce a generation of workers equipped to perform cost-effective audits (Wang & Cuthbertson, 2014; Washington, 2018). As part of a scholarly effort to address the audit community, this study will demonstrate how different types of data analytics techniques can improve decision making, effectiveness, and efficiency.

Nature of Study

This study directly collected and analyzed data from subjects who are expert, experienced IS audit professionals. It used this data to prove the cost-effectiveness of using analytics in the IS audit practice. This section explores the research method, theory, unit of measure and data collection approach used in this research. The research methods that were considered for this study include quantitative, qualitative, and mixed methods.

A quantitative study was not undertaken for this research because quantitative studies do not work well measuring perceptions regarding a specific phenomenon (Carrasco & Lucas, 2015). The mixed methods approach was also considered but not selected because it tends to produce results that may create a contradiction between the quantitative and qualitative approaches (Clark & Creswell, 2010). The researcher chose to conduct a qualitative study to elicit themes and concepts from IS audit practitioners to ascertain if using data analytics in IS audit could improve efficacy of the practice. A similar approach was used in a qualitative study by Golafshani (2003). According to Point, Fendt, and Jonsen (2017), the qualitative inquiry is rarely used in management science, but recent meta-studies have shown that a qualitative inquiry has the potential to generate higher-order knowledge and theory; hence the selection of the qualitative inquiry for this study.

The researcher used a survey with unstructured, open-ended questions to capture the perceptions of 27 ISACA IS auditors among. The purpose of the survey questions was to probe their perceptions on the use of data analytics in practice and how it impacts efficiency and cost-effectiveness of process (Cart, 2014). The unit of measure in this study was the individual survey participants' responses and their aggregated forms. Aggregating participants' responses to average their perceptions helped resolve discrepancies in responses (McClintock, Brannon, & Maynard-Moody, 1979). The researcher has been a member of ISACA since 2012, leading to the choice of that survey pool.

According to Creswell (2012), there are five different qualitative research methods: ethnographic, narrative, phenomenological, grounded theory, and case study. All these use similar data collection methods, and the difference lies in the purpose of the study, determining which specific method is best for a chosen research. Ethnography theory was considered for guiding this research, but it requires the involvement of the researcher in the natural environment over a long time to collect data (Pelto, 2016). That approach focuses on experiences of subjects concerning a phenomenon under study which would have worked in collecting IS auditors' experiences, but it is best used with unstructured face-to-face interviews. Phenomenological studies are used when collecting data from several individuals, who may have had similar experiences about a phenomenon under study, using interviews (Vagle, 2016, p.20). Considering most auditors travel for work, this method was deemed impractical.

The grounded theory approach was chosen for this study since it allows researchers to build new theories. This approach allows researchers to build new theories, revise existing ones, and advance research in policy and practice development (Parker, 2012). Thus, grounded theory enables the creation of a new paradigm that can reveal whether the use of data analytics automation can reduce IS audit process costs. This theory requires strict methods such as inductively labeling and categorizing data to produce a robust theory (Birks & Mills, 2015, p.16; Charmaz, 2014; Gallicano, 2013).

Grounded theory is divided into two parts: methods and products. The product portion follows four phases: data collection, open coding, axial coding, and selective coding. Open coding involves reading through the data several times to create labels; axial coding identifies relationships among open codes; and selective coding involves finding a core variable that summarizes all the data collected (Belgrave & Seide, 2018; Pace, 2016). The methods are described as coding procedures such as constant comparison, coding data into concepts and categories, use of interpretative frameworks, theoretical sampling, memoing, and combining categories into grounded theory (Vollstedt & Rezat, 2019).

Institutional Review Board (IRB) approval was requested before sending the study to participants. The survey questions were reviewed by experts in the field of IS audit and members of ISACA as a pilot study to ensure survey questions addressed the goals of this research. Data gathered from the pilot study was used to adjust the survey questions as necessary to more closely align with the purpose and goals of the study. Pilot data was used as validation of the survey instrument and to support the accuracy of the results of the final research (Boudreau, Gefen, & Straub, 2001; Van Teijlingen & Hundley, 2001). The survey was comprised of questions designed to address the research topic including demographic questions about basic professional profile and team size; level of use of data analytics on IS audit projects and the related cost levels; engagement of specialists (data analysts and data scientists) on IS audit projects; and significance of data analytics education and a standard framework in IS auditing (Susan& Robertson, 2016). The research questions section probed factors impeding cost-effectiveness and efficiency of the IS audit process.

Research Questions

This qualitative study explored the perceptions and experiences of IS auditors on factors affecting the use of data analytics in IS audit practice to minimize labor costs and improve audit process efficiency. The general question that this study addressed: how could the use of data analytics in information systems auditing improve efficiency and minimize costs? This general question breaks down into the following related questions:

RQ1: How can the application of data analytics in information systems (IS) audit improve the IS audit process?

The survey questions in RQ1 probed perceptions of IS auditors on the potential value of data analytics in IS audit process efficiency. The survey questions explored composition of IS audit teams concerning staffing sizes, effort required for data analysis tasks, and specialist skillsets required to provide full continuous assurance (DeAngelo, 1981; Hux, 2017; Sun, 2018; Sun & Vasarhelyi, 2018).

RQ2: Can the cost of labor be lowered in information systems (IS) audit by utilizing data analytics?

RQ2 sought to investigate ways by which data analytics could be used in IS audit practice to lower labor costs (Pathak, Chaouch, & Sriram, 2005; Pong & Whittington, 1994). Current advances in big data technologies and the proliferation of the internet of things (IoT), specifically the industrial internet of things (IIoT), have widened the attack surface for companies, hence the need for more cost-effective audit methods (Pasquier et al., 2018; Wilson et al., 2017). Manual labor such as preparation of electronic spreadsheets to prepare audit reports has become cumbersome due to the data proliferation.

RQ3: How could the use of a data analytics framework improve IS auditing?

RQ3 raised the concept of a framework that can guide the use of data analytics on IS audit engagements (Wang & Cuthbertson, 2014). A proposal for a predictive audit framework made by Kuenkaikaew and Vasarhelyi (2013) contends traditional audit practice is at best backward-looking compared to the promise of predictive auditing offering preventive measures. An IS audit data analytics framework would strengthen the organizational control environment through the enforcement of data analytics governance (Mangalaraj, Singh, & Taneja, 2014). The Statement on Auditing Standards (SAS) No.94 is a set of guidelines that provides adequate assessments of internal controls in IT systems. SAS No.56 communicates the need to analyze audit data availability, reliability, and predictability of relationships in data collected for audit purposes (Chew, 2015). SAS

Nos.94 and 56 could be leveraged as the foundation for developing an audit data analytics framework.

Theoretical Framework

Grounded theory was chosen to understand how data analytics could be used effectively to minimize IS audit labor cost. This required the collection and analysis of data to enable the emergence of a theory or theories grounded in the collected data. Grounded theory is proposed for this qualitative study because it uses constant comparative analysis and theoretical sampling (Hussein, Hirst, Salyers, & Osuji, 2014). The benefit of constant comparative analysis is raw data undergoes thorough continuous analysis until a theory emerges (Glaser & Strauss, 2017). Theoretical sampling involves iterative collection and analysis of data from which a theory emerges (Corbin & Strauss, 1990). Concurrent collection and analysis of data forces researchers to focus on the collected data rather than bringing in preconceived theories (Ramalho, Adams, Huggard, & Hoare, 2015; Thornberg & Charmaz, 2014).

The information technology assurance framework (ITAF) is a set of IS audit standards organized into three categories: general standards, performance standards, and reporting standards (ISACA, 2014b). ITAF provides a single source of professional guidance, research policies and procedures, and evidence reporting guidance (ISACA, 2014b). Where appropriate, under performance standards, it also provides guidance on the use of work from other experts. The ITAF framework was considered for this study, but its scope of focus is broad and does not provide guidance on the use of data analytics or technology in the IS audit process (Tchernykh, Schwiegelsohn, Talbi, & Babenko, 2016).

Control Objectives for Information and related Technology (COBIT) was also considered for this study since it is regarded as the premier framework for governance and management of enterprise information technology. While COBIT's core elements and principles make it a good enterprise governance framework for information technology, COBIT was not selected for this current study (Mutiara, Prasetyo, & Widya, 2017). COBIT lacks the technical foundation in data analytics in IS auditing (De Haes & Van Grembergen, 2015a). It also lacks the academic foundation to allow for grounded research studies; it is designed for practitioners' use (De Haes, & Van Grembergen, 2015a). Currently there is limited research using COBIT as a framework in conducting academic studies (Debreceny, 2013).

Definition of Terms

The following list of terms will help establish a clear understanding of the concepts of this study.

Assurance Services: Independent professional services that certify the validity of conformance to compliance requirements (Hasan, Maijoor, Mock, Roebuck, Simnett, & Vanstraelen,2005).

Attack surface: Attack surface in the context of information security refers to the scale of vulnerability an enterprise has and is comprised of the sum of the vulnerabilities that are exploitable (Chen, Qian, Mao, Tang, & Yang, 2016).

Audit Data Analytics (ADA): ADA is defined as "the science 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 to plan or perform that audit," (Staff, 2014, p.2).

Big data techniques: Data management and analysis techniques capture, wrangle, transform, and analyze data of different kinds (Gepp, Linnenluecke, O'Neill, & Smith, 2018).

Confirmatory data analysis (CDA): A set of traditional statistical analysis used to substantiate evidence for raised hypothesis (Jebb, Parrigon, & Woo, 2017).

Continuous monitoring: The automation of audit procedures, reporting, and data modeling (Cascarino, 2017).

Data analytics: A set of software tools and techniques used to analyze data. Alexiou (2016), contended data analytics is a must-have capability, which is divided into exploratory data analysis (EDA) and confirmatory data analysis (CDA). Data analytics is also divided into simple and advanced categories.

Deep learning: A class of machine learning algorithms using neural networks with many layers (Chartrand, Cheng, Vorontsov, Drozdzal, Turcotte, Pal, & Tang, 2017).

Exploratory data analysis (EDA): A set of traditional statistical analysis used for discovering patterns in data to foster hypothesis development and refinement (Camizuli & Carranza, 2018).

Haphazard Sampling: Sampling with no casual patterns nor subjective purpose, relying on convenience (Jia, & Zou, 2017).

Imbalanced data: A dataset that has categories which are not equally represented (Chawla, 2009).

ISACA: A professional association for executives in information systems governance, audit and control, and security assurance. It was formerly known as Information Systems Audit and Control Association, but it now goes by its acronym only.

ISACA was incorporated in 1969, and now serves over 140,000 professionals residing in 180 countries with more than 200 chapters in 80 countries (Darnton, 2017;Khan, Syal, & Kapila, 2006; Pilorget & Schell, 2018).

Machine learning: Computational methods leveraging experience to improve performance or to make accurate predictions (Mohri, Rostamizadeh, & Talwalkar, 2018, p.1).

Random Sampling: Involves selecting a sample from the population without replacement, giving every possible sample equal chance of being selected (Jia, & Zou, 2017).

Supervised learning: Computational methods that learn by training on labeled historical data to make predictions for all unseen points (Mohri, Rostamizadeh, & Talwalkar, 2018, p.6).

Technology Acceptance Model (TAM): A theory positing that an individual's behavioral intention to use an information technology tool or technique is predicated on perceived usefulness and perceived ease of use (Venkatesh & Davis, 2000, p1).

Text analysis: The process of extracting and analyzing plain text data to identify patterns that inform and guide audit assurance in corporate decision-making (Miner, Elder IV, & Hill, 2012, p.29).

Transfer learning: Learning a new task through the transfer of knowledge from a related task that has already been learned (Torrey & Shavlik,2010).

Unsupervised learning: Computational methods that learn by training on unlabeled historical data to make predictions for all unseen points (Mohri, Rostamizadeh, & Talwalkar, 2018, p.6).

Assumptions

Assumptions are presumed facts not verified or qualified by researchers (Ellis & Levy, 2009). Assumptions help researchers lay the groundwork for research, acknowledging that some unexplainable context cannot be verified beyond researchers' beliefs, yet the researcher deems these unproven facts to be practical (Flannery, 2016). The explicit assumption in this study was that responses from survey participants were truthful, hence valid. Using a survey for this study was assumed to be an appropriate method for enabling participants to be honest in their responses. The researcher also assumed that survey participants were aware of the components of data analytics and the extent to which data analytics can be used in auditing to analyze controls. Qualitative studies use validity assessments to determine the accuracy and reliability of participants' responses (Ellis & Levy, 2009). The validity of the quality of the responses from participants was assumed to be high because ISACA is considered the leading institution for information system audit and control in the world (ISACA, 2014). American Institute of Certified Public Accountants (AICPA) was also considered because it develops standards for audits of private companies and other services by certified public accountants, but its mandate is focused on the accounting profession (Cooper & Sherer, 1984).

Scope, Limitations, and Delimitations

Scope, limitations, and delimitations help form a framework clarifying research credibility (Ellis & Levy, 2009). The scope of this qualitative study was focused on examining the factors perceived to be affecting the adoption of data analytics in the IS audit process. Due to the deficiencies inherent in qualitative research, the generalizability of the findings may be open to question. It was impossible to guarantee a truly random survey sample since respondents were volunteers. Analysis by geographic location of participants was not possible since the survey was posted on LinkedIn, a global social media site. Survey participant selection by education relevance was limited to possession of an ISACA certification, since certification requirements include having a 4-year degree or equivalent in experience. However, the approach of this study allows deep insight into participants' responses that can be applied to subsequent quantitative research for generalization (Gallicano, 2013). These limitations to some extent can be controlled by the researcher, to help establish parameters of the scope of the study (Theofanidis & Fountouki, 2018).

Several delimitations were applied to the scope of this study. First, the research was confined to the use of data analytics in the IS audit process due to the enterprise information systems environments. The second was the researcher considered quantitative and mixed methods approaches but did not use them because the goals of the study sought to examine perceptions of the IS audit practitioners regarding the use of data analytics. Third, the researcher did not use the phenomenological method because it is best used with unstructured face-to-face interviews (Vagle, 2016, p.20). The researcher did not conduct interviews because of the time needed to conduct interviews and transcribe them for coding and difficultly in scheduling with auditors who often travel. Fifth, ethnography theory was not used because it requires the involvement of the researcher in the natural environment over a long time to collect data (Pelto, 2016). The sixth was the exclusion of other audit professionals such as financial and internal auditors because high labor cost and poor process efficiency particularly affect IS auditors more due to the rapid proliferation of big data technologies. The seventh delimitation was the study did not focus on any specific tasks of the IS audit process to allow for an overall view of all tasks. The researcher did not use triangulation to ensure data saturation because the target population was diverse enough to provide validity. Finally, the researcher did not limit the study to any specific industry as IS audit involves the same patterns across different business environments.

Chapter Summary

Although the use of data analytics in the audit industry has grown rapidly over the past two decades, the practice has been slow to deploy it (Byrnes et al., 2018). Related literature contends that analytics can be used as part of the accounting audit strategy to reduce labor cost, improve efficiency, and prevent fraud (Boritz et al., 2013). The rapid growth in the volume of data, the increased data velocity, the variety of data types, and the explosion of IoT implementations and usage across the industry over the past decade has widened the attack surface (Liu, Cronin, & Yang, 2016; Liu, Yang, Zhang, & Chen, 2015; Zhang et al., 2014). The IS audit practice faces daunting challenges in the near future if data analytics are not made available to the general population of practitioners (Cronin, & Yang, 2016). The rising cost of engaging data scientists and data analysts on IS audit projects will make it difficult for teams to provide efficient and cost-effective projects. The grounded theory qualitative approach will be used to develop a conceptual framework to explore data analytics in IS audit. Chapter 2 will explore current trends and the use of data analytics in IS audit.

CHAPTER 2: LITERATURE REVIEW

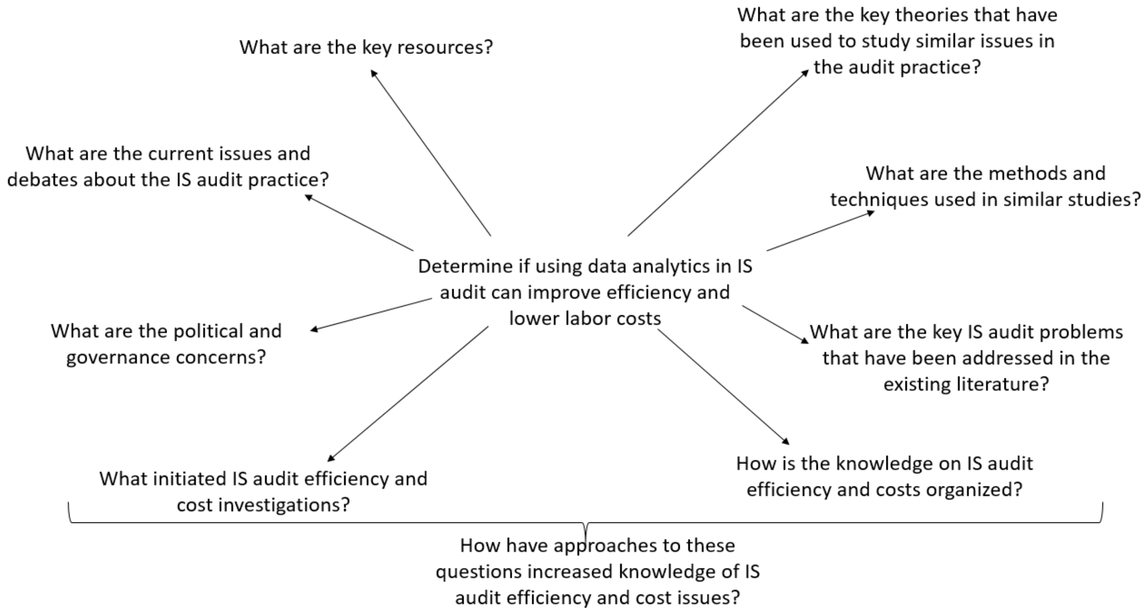
This chapter discusses the literature which provided the basis for the study to establish how the use of data analytics in the IS audit process can help minimize labor costs and improve efficiency. The synthesis of literature supports or refutes findings from other studies (Hart, 2018, p.3). Cronin, Ryan, and Coughlan (2008) define the literature review as an objective critical analysis of existing scholarly research relevant to a subject under study. The literature review summarizes the research methods introduces a range of techniques and methods that have wide usage in related studies (Hart, 2018, p.3).

The majority of this chapter is comprised of a theoretical orientation for the study and the actual literature review work. The review of literature along with a critique of existing findings and research methods justified and established the significance of the study and research methodology used by the researcher (Ramdhani, Ramdhani, & Amin, 2014). It consists of a critical analysis of the IS audit process, IS audit frameworks, data analytics techniques, and concludes with a chapter summary of research related to IS audit effectiveness and labor cost minimization.

Appendix A shows a table of the literature searches by themes and groups. Appendix D contains a literature map that guided the review for each of the sections in this chapter. The map is a detailed expansion of Figure 1 which establishes the core framework for tying together literature selected for the study.

Figure 1 provides a framework for guiding the literature review to address the goals of this study.

Figure 1. The approach adopted in this literature review



Title Searches

This study made use of a number of academic and audit practice resources. The primary resource was Capitol Technology University's (Captech) virtual library, which is a collection of several online academic libraries. Some of the resources accessible in Capitol Technology University's virtual library include EBSCO open dissertations, Capitol Technology University OPAC, LexisNexis, ProQuest databases and journals, Taylor and Francis, Business Source Premier, ACM DL, IEEE Computer Society, dissertations, and Thesis Full Text. This study supplemented Capitol Technology University's virtual library resources with research libraries available from ISACA and the American Association of Accounting Journals, Google Scholar, Research Gate, Science Direct, and the Project Management Institute's (PMI) research library. As a member of ISACA and PMI, the researcher had access to peer-reviewed journal articles from these two institutions. The researcher sought out literature that examined IS audit, the use of data analytics, information assurance frameworks, IS audit labor patterns, regulatory compliance, audit and analytical technologies, and research methods. The study also made sparing reference to dissertations as primary sources.

Articles

This research study selected 240 articles from largely peer-reviewed journals, dissertations, and books. The researcher also used some recent news articles and popular weekly columns from McKinsey & Company and Gartner & CEB. A summary of the literature reviewed is in Appendix A. While most of the journal articles reviewed were published within the last five years, the literature reviewed in this study goes back as far as 1921.

Research Documents

The researcher used official documents issued by ISACA, ITGI, ISO, and NIST for references to current information assurance and audit frameworks. ISACA's governance frameworks were found in COBIT documents, IT risk framework and VAL IT framework, while references to NIST were found in Special Publications (SPs) documents. The Audit frameworks section below provides full descriptions of methodologies associated with the listed documents.

Journals Researched

This study references articles from both U.S. and international management information systems journals. Most of the U.S. journals used in this study are from the American Accounting Association (AAA). Founded in 1916, the AAA is considered the largest community of accountants in academia (Brown, Coram, Dennis, Dickins, Earley, Higgs, & Tatum, 2019). AAA's audit related research is published through Current Issues in Auditing which is dedicated to advancing research and dialogue between academics and practitioners on audit challenges and opportunties. Some specific international journals utilized were: Administrative Science Quarterly, African Journal of Economic and Management Studies, Association for Computing Machinery (ACM), Behavioral Research in Accounting, Cengage Learning, Future Generation Computer Systems, IEEE Transactions on Engineering Management, International Journal of Accounting Information Systems, International Journal of Basic and Applied Science, International Journal of Engineering & Technology, Issues in Informing Science & Information Technology, Journal of Big Data, Journal of Business Research, Journal of Computational Science, Journal of Emerging Technologies in Accounting, Journal of Information Systems, Journal of Practice & Theory, MIS Quarterly Executive, MIT Sloan Management Review, and Qualitative and Quantitative Methods in Libraries (QQML). A brief history of the information systems audit is discussed below.

Historical Overview

This section reviews the history of the information systems (IS) audit practice and its current state. IS audit as a practice traces its origin to the early 1960s when auditors began monitoring computerized accounting systems (Maxson, 1978). The field started as electronic data processing (EDP) auditing (Weber, 1998, p.34). An increase in computer use in the mid-1960s gave birth to the Electronic Data Processing Auditors Association (EDPAA) (Byrnes et al., 2018; Groomer & Heintz, 1994; Halper, 1985; Horowitz, 1970). The purpose of EDPAA was to provide IS audit standards, guidelines, and procedures (Sayana, 2002). To formalize EDP auditing the association developed a set of control objectives which became known as the COBIT framework. ISACA was born from EDPAA (DeFond & Zhang, 2014). The rapid growth in information technology since the 1960s has brought many changes to the field. COBIT, first released in 1996, is one of the early audit frameworks originally developed to establish control objectives for IT business environments (De Haes, Van Grembergen, Joshi, & Huygh, 2020).

Audit Frameworks

COBIT is regarded as the leading governance and IT management framework for business and was developed by ISACA and the Information Technology Governance Institute (ITGI) (De Haes, Huygh, Joshi, & Van Grembergen, 2016; De Haes & Van Grembergen, 2015a). COBIT is considered the “gold standard” in IS assurance, although some recent studies pointed out the lack of challenge to the underlying concepts of COBIT as a major weakness (De Haes et al., 2016). Recent studies have raised questions about the validity of COBIT in IS assurance and auditing (Merhout & O’Toole, 2015). The applicability of COBIT 5 to minimize audit costs and improve efficiency has specifically been questioned (Debreceny, 2013; Mangalaraj et al., 2014). COBIT 5, published on April 10, 2012, is the latest version of the framework, designed to enable effective governance of enterprise IT (Oliver & Lainhart, 2012). De Haes and Van Grembergen’s main contention is that adopting COBIT 5 as a governance and guiding framework in IS auditing requires considerable effort, deeming it complex and costly (De Haes & Van Grembergen, 2015b). That contention sparked the central theme of this study, which intends to ascertain if using data analytics can improve audit process efficiency and minimize concomitant labor costs.

Mangalaraj, Singh, and Taneja (2014) argue that COBIT is impossible to study because empirical research on this extensive framework requires large datasets. The sheer magnitude of the controls impedes the efficiency of the audit process (Mutiara, Prasetyo,

& Widya, 2017). Other IT governance frameworks competing with or complement COBIT, namely: ITIL, ISO, COSO, NIST-RMF, and ISACA's ITAF (Chou, 2015). The adoption and implementation of any specific framework has a bearing on the efficiency of processes as well as the costs associated with the use of a specific framework (Radhakrishnan, 2015; Yin, 2015).

Regulations

An investigation of the regulatory requirements that play a part in the IS audit process - effectiveness, efficiency, and labor cost, reveal the Sarbanes-Oxley Act (SOX) of 2002 as one of the costliest regulations in the history of the practice (Kokash, 2014). SOX is a United States federal law enacted on July 30, 2002, which was sponsored by U.S. Senator Paul Sarbanes, a Democrat from Maryland, and U.S. Representative Michael G. Oxley, a Republican from Ohio (Act, 2002). There are similar laws in other countries that are worthy of note in the context of IS audit process effectiveness, efficiency, and labor costs. The list includes Canada's Bill 198, Japan's J-SOX, Australia's CLERP9, South Africa's King Report, Europe's Directive No.8, the European Union's General Data Protection Regulation (GDPR), and California's Consumer Privacy Act (CCPA) (Carey, Monroe, & Shailer, 2014; Huang, Zavarsky, & Ruhl, 2009; Jordan, Clark, & Waldron, 2014; Rensburg & Botha, 2014; Team, 2017, p.252; Voigt & Von dem Bussche, 2017). Given that Canada's Bill 198 (C-SOX) is less stringent on external auditor attestation of internal control adequacy, it is less costly on labor compared to the United States' SOX (Bhabra & Hossain, 2018). Japan's J-SOX and Europe's Directive No.8 borrowed many properties from the United States' SOX law; therefore, they all carry the same level of labor cost burden on audits (Coates & Srinivasan, 2014).

SOX Section 404 requires auditors to select and use a suitable internal control framework to comply with its requirements (Fan, Li, & Raghunandan, 2017). Section 404 is split into two parts: 404a and 404b. Section 404a mandates management to conduct an internal annual operational effectiveness while 404b requires external independent auditors' report of internal controls (Levy, 2016). The major issue with Section 404b is the increased labor cost inevitable audit fees that companies must pay to comply with this Act's requirements (Kinney& Shepardson, 2011; Kravet, McVay, & Weber, 2018). Following the enactment of SOX 404b, audit fees increased 100% for non-exempt firms due to the increase in labor required to carry out internal control tests and evidence analysis (Kinney & Shepardson, 2011). These higher audit fees are due to the labor intensiveness of complying with SOX (Barr-Pulliam, Brown-Liburd, & Sanderson, 2017; Länsiluoto, Jokipii, & Eklund, 2016; Zhao, Bedard, & Hoitash, 2017).

While there is a substantial fixed cost associated with the implementation of SOX Section 404b, smaller public companies have been exempt from implementing it since June 2007 (Willits & Nicholls, 2014). Kinney and Shepardson (2011) found that organizations exempt from SOX Section 404b incur only a small fraction increase in audit fees but non-exempt organizations need bigger audit teams manually reviewing internal controls. Jaara and Oweis (2016) investigated ways to lower the cost of conforming to SOX 404 and how it affects investors' confidence since non-exempt organizations incur higher external audit fees. Their study found the enactment of Dodd-Frank has decreased SOX 404b compliance costs for non-accelerated filer firms because of the enforcement of permanent exemption. Securities and Exchange Commission (SEC) classify firms with public floats less than $75 million as non-accelerated filers (Nakamizo, & Zhu, 2018).

Although SOX Section 404 has a broad focus on auditing and financial regulations for public companies, it does not establish technological approaches and techniques to be used in the audit effort to comply with the regulation. IS audit could leverage data analytics to mine for SOX and other regulatory compliance violations (Barr-Pulliam, Brown-Liburd, & Sanderson, 2017). An auditing approach that conducts process mining can heavily leverage data analytics to identify anomalies from event logs and streamline SOX compliance (Jans, Alles, & Vasarhelyi, 2014).

In addition to SOX regulations, GDPR and CCPA are further examples of government regulations imposing increased costs on firms due to the numerous regulatory requirements ((Burattin, Van Zelst, Armas-Cervantes, Van Dongen, & Carmona, 2018; Chen & Khurana, 2017). Professional institutions and industry regulators may also increase operational costs to business by introducing standards, guidelines, and procedures from (Abou-Seada & Abdel-Kader, 2017; Firescu & Popescu, 2015). The adoption of the International Financial Reporting Standards (IFRS) and United States Generally Accepted Accounting Practices (US GAAP) are associated with rising audit cost and poor efficiency (Khlif & Achek, 2016).

The establishment of the Auditing Standards Board (ASB) in October 1978 by the American Institute of Certified Public Accountants (AICPA) brought about the Statements on Auditing Standards (SAS) No.94 (AICPA, 2017). This is a set of guidelines that suggests assessments of internal controls in IT systems (Cerullo & Cerullo, 2003). It provides guidance on how the use of IT and manual procedures affect the audit process and internal controls in a financial statement audit (Le & Lehmann, 2016). IS auditors would benefit from using data analytics to meet the internal control needs of their clients' guidelines of SAS No.94 (Kiesow, Fellmann, Zarvic, & Thomas, 2015).

Another guiding standard is SAS No.56 which requires the use of analytical procedures in the planning and review of audits (Abou-Seada & Abdel-Kader, 2017). SAS No.56 mandates the need to analyze audit data's availability and reliability, as well as the predictability of relationships in data collected for audit purposes (Chew, 2015). Data analytics can provide the tools to simplify the requirements of SAS No.56 (Hoogduin et al., 2014; Yoon, Hoogduin, & Zhang, 2015). Modern data analytics toolsets offer predictive and correlational capabilities that can be used to test relevency and reliability of audit data to comply with SAS No.56 (Yoon, Hoogduin, & Zhang, 2015).

Starting 25th May 2018, the European Union (EU) instituted and enforced the General Data Protection Regulation (GDPR) to protect EU residents' personal information (McGregor & Zylberberg, 2018, Voss, 2017). This regulation is deemed the most significant data protection act in the world, as it is enforceable outside EU member states and requires any organization providing services involving EU residents to comply (Beacham, 2018). The two key objectives of the GDPR are (1) to protect the rights, privacy and freedoms of EU residents and (2) to enable free movement of data throughout the EU to reduce barriers to business (Černá & Sieber, 2018; Finck, 2018). According to Banakar, Shah, Shastri, and Chidambaram (2019), GDPR's significant impact on data storage and processing increases labor costs for audit and compliance. GDPR requires a strict audit and compliance practice, which not only requires substantial investment to implement, but will involves some major data governance process changes (Banakar, Shah, Shastri, & Chidambaram, 2019). To quote from Samuel Butler's 1877 book "Life and Habit", "In law, nothing is certain but the expense". Leveraging data analytics in auditing GDPR-related compliance requirements could help reduce the cost of compliance.

Current Findings

Findings from existing literature clearly illustrate issues regarding labor cost and efficiency in the IS audit practice. Current literature also helps to establish the need for this study by exposing gaps and strengths of existing studies which will shape advances in future research in IS audit field. Existing literature provides theories, methods, and techniques commonly used in IS audit research.

Current Issues and Debates about the IS Audit Practice

Dzuranin and Mălăescu (2016) conducted a qualitative study that surveyed 30 academic researchers and 15 audit practitioners to examine the current and future state of IS audit research and practice. In the qualitative study, the researchers provided a synthesis of the key themes and possible research questions. Two major issues discussed were (1) the role of IS auditors in regulatory compliance assurance and IS value delivery and (2) the role of advanced data analytics and emerging technologies in the future of the IS audit process.

The foundation of this current study traces its origins to one of the key findings of Dzuranin and Mălăescu (2016). Their discussion asserts that during a 1000-hour job, 90 percent of the time will be spent on understanding data (Dzuranin & Mălăescu, 2016). Some similar studies in support of Dzuranin and Mălăescu (2016) contend firms need to adapt and change business strategies and decision-making processes to improve the audit process in the wake of data analytics (Griffin & Wright, 2015; Moffitt & Vasarhelyi, 2013).

Dzuranin and Mălăescu's (2016) study employed a framework that directed future research to well-established and emerging practice issues. The research framework approach has parallels to this current study in building theories to understand how certain processes work (Geerts, Graham, Mauldin, McCarthy, & Richardson, 2013). A major shortcoming of the Dzuranin and Mălăescu (2016) study is that it did not demonstrate the actual building of the theory from the data gathered. There was also no specific data analysis method used to analyze the discussion.

Kim, Teo, Bhattacherjee, and Nam (2017) conducted a quantitative study that sought to address factors that influence audit satisfaction on IS projects. Kim et al. (2017) proposed an IS audit satisfaction model that included auditor expertise, auditor role clarity, audit responsiveness, and audit reliability. The study used data collected from 203 South Korea (SK) public sector IS projects to test the model. One of the findings from Kim et al. (2017) raised a key research question: "How can an IS audit be effectively and efficiently conducted in a semantic and syntactic manner?" This current study will seek to understand how the use of data analytics in the IS audit process can help to minimize labor cost and improve efficiency. A significant limitation of Kim et al.'s (2017) study is the lack of generalizability of the research results because the study's analysis was based only on South Korea's public sector organizations. Another shortcoming of the study was the absence of technology's influence on the proposed IS audit research model and, specifically, data analytics.

Verver (2008) strove to provide a data analytics strategy for audit analytics with a qualitative study. The study summarized steps to establish best practices for audit analytics while arguing that IS audit is no longer a separate practice from mainstream financial auditing. Verver (2008) further contends that training in the effective use of technology in general and specifically data analytics in particular is a critical factor to the successful adoption of data analytics in auditing. The study emphasized the advantage of being able to examine 100 percent of transactions in the audit process as a fundamental benefit of using data analytics. Related research by Shaikh et al. (2018) agrees with Verver that the ability to examine 100 percent of the data transforms the IS audit process. Chan and Vasarhelyi (2011) also concurred with Verver, referring to the opportunity to automate much of the audit as a significant benefit due to improved efficiency, consistency, and the quality. According to Verver (2008), the benefits of using data analytics in the audit process fall into five main categories: improved productivity; cost savings; better quality; increased independence; audit risk reduction; and supporting internal audit's changing role. The limitation of Verver's (2008) study is there is no apparent source of the data that was used in the study. The study does not methodically examine the data, even though it does propose solutions to issues in traditional audit analysis.

Titera (2013) conducted a qualitative study that explored the emerging role of data analytics in the audit process. Titera (2013) proposed revision of current audit standards to enable effective use of data analytics for cost-effective auditing. Titera (2013) further argued that current audit standards as described in SAS No. 56 AU Section 329 inhibit effective use of analytics which offers timely and quality audit evidence.

Specifically, the author contends that current audit standards should be updated to address the use of audit data analysis, elaborating on when, where, and how data analysis should be leveraged in planning, execution, reporting of audit evidence, and continuous auditing. According to Titera (2013), data analysis could be the best alternative for anomaly and outlier detection versus traditional procedures such as “fraud brain-storming sessions and perfunctory journal entry testing” (Titera, 2013). The limitation to Titera’s (2013) qualitative study is that no data was used to support the claim for the need to update audit standards.

Porte, Saur-Amaral, and Pinho (2018) researched the main thematic trends in research in audit practice literature from historical to current trends. Their content analysis reviewed established, declining, and emerging themes. The study investigated the popularity of themes in audit research between 2002 and 2014. The findings of the study discovered 22 themes, an increase of eight prior to the enactment of the SOX Act in 2002. The 22 themes are as follows: audit committee; audit market; audit procedures; audit report and financial statement users; audit sampling; auditor's judgment; auditor-auditee contract; corporate governance; education; external audit; fraud risk and audit risk; going-concern opinion; internal audit; internal control; international regulation; liability and litigation; media coverage in accounting; non-audit services; profession; research; socio-economic data of the company; and tax audit. These themes establish research guidance and the hierarchy of current issues in IS audit practice.

Porte, Saur-Amaral, and Pinho (2018) discovered three journals contributed the most themes. The three journals in order of the most contributions were *Auditing: A Journal of Practice & Theory, Contemporary Accounting Research, and Accounting*

Review-Journal. These three journals were among 1,650 publications from the Web of Science published from 2002 to 2014. The themes that dominated the top ten in Porte, Saur-Amaral, and Pinho (2018)'s literature review included audit report and financial statement users; corporate governance; external audit; socio-economic data of the company; audit market; international regulation; fraud risk and audit risk; audit committee; profession; liability and litigation. The findings from Porte, Saur-Amaral, and Pinho (2018) included internal control in the list of themes that are driving recent IS audit research. Internal control is one of the key requirements of SAS No. 94.

Table 1 below summarizes the literature examined for this study that focused on the current issues and debates about the IS audit practice. The summary captures the authors, methodology, and findings.

Table 1

Summary of Current Issues and Debates about the IS Audit Practice

Authors	**Methodology**	**Findings**
Dzuranin and Mălăescu (2016)	Qualitative	• During a 1000-hour job, 90 percent of the time is spent on understanding data. • Firms need to adapt and change business strategies and decision-making processes in the presence of data analytics which in turn impacts the audit process.
Kim, Teo, Bhattacherjee, and Nam (2017)	Quantitative	• "An IS audit can be effectively and efficiently conducted semantically and syntactically" (Kim et al., 2017).

Table 2

Summary of Current Issues and Debates about the IS Audit Practice Continued

Authors	**Methodology**	**Findings**
Verver (2008)	Qualitative	• Best Practices for the Use of Data Analysis in Audit. • 100 percent audit data examination. • Efficiency and effectiveness. • Transforming internal audit into IS audit.
Titera (2013)	Qualitative	• Proposed revision of current audit standards to enable cost effective IS audits. • Emphasized the role of data analytics in the audit process.
Porte, Saur-Amaral, and Pinho (2018)	Qualitative	• The findings of the study discovered 22 new auditing themes, an increase of eight themes prior to the enactment of the SOX act in 2002.

Benefits of Data Analytics in the IS Audit Practice

Earley (2015) explored opportunities and challenges of data analytics in auditing, proposing companies invest in this science. Auditing is a heavily regulated area, which explains the hesitation to adopt analytics (Earley 2015). Earley contends that data analytics can help auditors test larger proportions of enterprise data. In a related study Capriotti (2014) made similar assertions about audit data sample sizes and the quality of audits heavily relying on analytics. A study by Gray and Debreceny (2014) supported Earley's findings when they also concluded that it is easier to detect fraud through data analytics. In addition to the noted findings, Earley (2015) also argued that there are three broad obstacles to the widespread adoption of new techniques in auditing: training and expertise; data availability and relevance, and regulatory requirements. However, a study by Katz (2014) cautioned that regulators worry that training auditors on analytic techniques may reduce emphasis on audit requirements by shifting focus away from auditing. Earley's (2015) qualitative study quoted case studies, but the study did not collect its own data. There was no indication the study attempted to employ any specific theoretical framework. Nevertheless, the effort provided a literature review that shed light on the factors affecting the adoption of new audit practices.

Sun and Vasarhelyi (2018) conducted qualitative exploratory research that examined the value of textual data in audit evidence analysis and introduced deep learning as a data analytics technique. The study is an explanatory summarization of the value of IS analytics in auditing. Deep learning enables machine learning models and algorithms to learn from experience to solve problems using a hierarchy of concepts (Goodfellow, Bengio, Courville, & Bengio, 2016, p.12). However, the Sun and Vasarhelyi (2018) study lacked a systematic literature review method and a theoretical framework. Typically, qualitative research studies demonstrate extensive systematic literature synthesis based on an established theoretical framework (Kitchenham et al., 2009).

Gepp, Linnenluecke, O'Neill, and Smith (2018) conducted a systematic literature review aimed at investigating the use of data analytic techniques in general auditing, and they concluded that these methods are infrequently used. A possible explanation for this lag could be that the practice needs to align with technologies in use by current clients (Alles, 2015). Gepp et al. (2018) also introduced big data techniques, specifically data analytics and multivariate statistical literature for possible applications in auditing. Gepp et al.'s (2018) study explored the use of techniques such as unsupervised and supervised learning in auditing to reveal problems and predict risks. A study by Yang, Yu, Liu, and Wu (2018) concurred with Gepp et al. (2018) claiming that new sources of evidence such as social media data require specialized analytics techniques to carry out an audit. An earlier study by Gray and Debreceny (2014) had also claimed that advances in natural language processing (NLP) promise enormous benefits to the audit practice and could be used to influence new fraud detection models using textual data. The Gepp et al. (2018) literature review was comprehensive, although no data was collected for the study. It could have provided a better in-depth analysis had it not generalized big data techniques, but rather focused on a specific technique. Overall, Gepp et al. (2018) provided an in-depth exploration of the advanced data analytics techniques and tools that could be valuable to process efficiency and costs.

Singh, Cheng, and Lai (2017) conducted a case study of rule-based fraud detection techniques by developing an anomaly detection model to analyze accounting data in a procurement system. They found that the anomaly detection model successfully carried out 100 percent testing of data in a short period, leading to a faster audit. Singh et al.'s (2017) study also found the use of analytic techniques improved the quality and efficiency of audits and afforded important insights into the entire process. Singh et al. (2017) contends that shortcomings in audit team skill sets and technology resources contribute to diminished quality if teams do not leverage data analytics. Singh et al.'s (2017) study parallels this current study, which seeks to establish how the use of these techniques in the IS audit process can help to minimize labor cost and improve efficiency.

Singh et al. (2017) also confirmed the importance and applicability of data analytics in continuous auditing. It was a case study comprising five participating audit teams. While it discussed the data that was collected from the SAP procurement system, it did not elaborate on the type of analyses that were carried out to derive the conclusions and findings. The related theory and method of study were also not identified.

Sirois and Savovska (2018) from the Audit Training of Trainers community explored the benefits of using data analytics in auditing. Their study listed the following three key benefits to the audit practice: enhanced audit quality; increased audit effectiveness; and improved client service. Sirois and Savovska (2018) focused on the following three research questions: 1. “How is technology transforming the audit?”, 2. “What is new about audit data analytics?”, and 3. “What benefits do audit data analytics bring to practitioners?”

In Sirois and Savovska’s (2018) study, research question number one shed light on increasing hardware and software inputs and the need for data analytics to introduce new forms of audit evidence and new audit testing techniques. The second research question dealt with the new trends and techniques inherent in the use of data analytics. Some of the techniques included statistical procedures such as exhaustive cluster analysis, predictive modeling, visualizations, and data layering.

The third question addressed the benefits audit data analytics brings to practitioners, which is the core of the article. Several benefits were identified regarding the increased effectiveness of audits, including greater relevancy, easier issue identification, quick assessment of large volumes of data, increased auditor focus, more frequent testing, and timely reporting of audit findings. Some concerns that were identified in the study included instances of auditors claiming that they had difficulties in fitting data analytics-derived audit evidence into the current (ISA) 520 analytical procedures evidence framework. Eimers (2016) had noted similar difficulties with fitting statistical results into the compiled audit evidence. Overall, Sirois and Savovska (2018) reinforce Singh et al.'s (2017) findings on the significance of audit data analytics. Shortcomings of Sirois and Savovska's (2018) article lie in its failure to employ a theoretical foundation of the derivation of its findings. The strength of the article was in the use of international audit standards from ISA.

Perols, Bowen, Zimmermann, and Samba (2017) conducted a quantitative research that explored the use of data analytics to improve fraud prediction. Perols et al.(2017) explored three significant issues in developing fraud detection models: (1) the unusual nature of fraud observations in data, (2) the abundance of predictor variables identified in existing literature, and (3) the difficultly in defining what constitutes fraud. Perols et al. (2017) found that using multi-subset observation helps to address fraud data rarity issues, demonstrating that the "curse of dimensionality" in having too many predictors can be solved by using a backward feature selection method, and the broadness of the definition of fraud can be addressed by partitioning fraud into types using data analytics. Perols et al.'s (2017) quantitative experimental design study analyzed more than 10,000 financial fraud prediction models which leveraged data from 51 fraud firms, 15,934 non-fraud firm-years, and 109 predictor variables from prior studies. The most relevant finding in Perols et al's (2017) study is that using data analytics in financial auditing improves fraud prediction performance by 10 percent compared to conventional techniques. Therefore, Perols et al.'s (2017) findings demonstrated that using data analytics in fraud detection improves efficiency.

The limitation of Perols et al.'s (2017) study did not explore cutting-edge techniques of dealing with imbalanced data such as transfer learning and synthetic data generation popularized by Amazon Mechanical Turk (AMT) (Buhrmester, Talaifar, & Gosling, 2018). In the case of the "curse of dimensionality," other new techniques could be explored, such as genetic algorithms and natural language processing, especially when dealing with unstructured and semi-structured data (Sakthivel, Nair, Elangovan, Sugumaran, & Saravanmurugan, 2014). The other limitation of Perols et al.'s (2017) study was the lack of theoretical framework guidance in building the study.

Appelbaum, Kogan, and Vasarhelyi (2017) explored research needs regarding the use of big data and analytics in modern audit engagements considering most business systems are now integrated with the cloud, Internet of Things, and social media. Appelbaum et al.'s (2017) qualitative study was motivated by the promise of data analytics to enhance and replace traditional manual audit procedures. They also asserted the rapid proliferation of big data and advanced analytics created limitless opportunities for auditors to use data analytics (Appelbaum et al., 2017). Appelbaum et al. (2017) also developed a synthesis of big data analytics, internet of things, the cloud, and social media concerns in the audit community. However, they did not collect or use any other data apart from a systematic review that amalgamated and explored existing literature.

Bailey, Collins, and Abbott (2017) investigated benefits of ERM in reducing audit fees and the minimization of audit delays. Bailey et al. (2017) argued that the client's

ERM has a significant positive influence on audit efficiencies compared to internal controls. They further found that poor ERM quality has a significant negative impact on audit fees and audit efficiency. Bailey et al. (2017) approached audit process efficiency from an enterprise risk management perspective, whereas this current study is examining audit process efficiency from the perspective of the use of data analytics. The IS audit process is often part of the overall enterprise risk management in any organization; therefore, the use of data analytics in the process would impact ERM value streams.

Table 2 below is a summary of studies that investigated the benefits of data analytics in auditing. The summary captures authors, methodology, and findings of each study.

Table 3

Summary of Studies on Benefits of Data Analytics

Authors	**Methodology**	**Findings**
Earley (2015)	Qualitative	• Regulators fear big data threatens audit quality. • Auditors can test larger proportion of enterprise data. • Easier fraud detection through data analytics.
Sun and Vasarhelyi (2018)	Qualitative	• The value of deep learning in auditing. • The value of textual data in providing additional audit evidence. • Introduced approaches on how to leverage deep learning in IS auditing.

Table 4

Summary of Studies on Benefits of Data Analytics Continued

Authors	**Methodology**	**Findings**
Gepp, Linnenluecke, O'Neill, and Smith (2018)	Qualitative	• Multivariate statistical literature that recommends possible applications of data analytics in auditing.
Singh, Cheng, and Lai (2017)	Qualitative Case Study	• Exhaustive testing of data leads to faster audit. • Importance of time-series and cross-sectional analyses in improving audit effectiveness.
Sirois and Savovska (2018)	Qualitative	• Data analytics enhance audit quality. • Improved client services. • Increased effectiveness.
Perols, Bowen, Zimmermann, and Samba (2017)	Quantitative	• Three data preprocessing methods. • 10% improvement in fraud prediction compared to current. • Improved ability of the Securities and Exchange Commission (SEC) to detect fraudulent filings. • Can improve audit firms' client portfolio decisions.
Appelbaum, Kogan, and Vasarhelyi (2017)	Qualitative	• The need to establish new audit standards that use audit data analytics. • The promise of 100 percent testing of data for auditing.

Table 5

Summary of Studies on Benefits of Data Analytics Continued

Authors	Methodology	Findings
Bailey, Collins & Abbott (2017)	Quantitative	• The Impact of Enterprise Risk Management (ERM) on the Audit Process. • Benefits of ERM in reducing audit fees and minimization of audit delays. • Evidence of higher Audit Fees

Theories, Methods, and Techniques in IS Audit Research

Axelsen, Green, and Ridley (2017) conducted a field study on the perceptions of the role of IS auditors in financial audits. The participants in this study were 55 senior auditors in public sectors in Australia, Canada, the United Kingdom, and New Zealand. The study used semi-structured interviews to collect data from the participants with open-ended questions to probe perceptions of the IS auditor's role. The qualitative study addressed the research questions by developing an explanation theory which sought to define the role of the IS auditor in a financial audit. Axelsen, Green, and Ridley's (2017) theoretical analysis approach also intended to explain the role of the IS auditor in a financial audit.

Axelsen et al. (2017) developed the explanation theory using a grounded theory approach in five stages: thematically coding statements collected from semi-structured interviews; manually categorizing and coding subsets of the interviews; extending coding through the machine; identifying common statements from responses; and generating the theory of explanation. Extending coding through the machine, in this case, refers to the creation of machine-learned classifiers from manually coded subsets. This particular research used semi-structured open-ended questions to probe responses from professional auditors, and analyzed the collected data by open coding, axial coding, and selective coding. The distinct difference between the explanation theory and the grounded theory is that the latter uses constant comparative analysis and theoretical sampling where data collection and analysis are done simultaneously (Axelsen, Green, & Ridley, 2017; Glaser & Strauss, 2017). Leveraging the grounded theory in this current study used insights from initial data analysis, which helped to recruit more participants with differing perceptions about the use of data analytics in the IS audit (Beattie, Fearnley, & Hines, 2015).

The development of the explanation theory in this study established its foundation from the work of Gregor (2006). Gregor (2006) explored the nature of theory in information systems by distinguishing between five interrelated types of theory: the theory of analyzing; the theory of explaining; the theory for predicting; the theory for explaining and predicting; and the theory for design and action. Gregor (2006) contends that the theory of explanation clarifies how and why a certain phenomenon occurs.

Cho and Lee (2014) conducted a qualitative study that compared and delineated the relevant research goals and rationale for choosing between the grounded theory and qualitative content analysis methods. Qualitative content analysis provides the flexibility to use an inductive or deductive data analysis approach while extracting latent content meaning (Cho & Lee, 2014). In much of the current research, qualitative content analysis has been used to test existing theory and to interpret meaning from data (Schreier, 2012, p.2). On the other hand, the grounded theory is used when no theory exists or the theory is too broad to be examined (Cho & Lee, 2014). Cho and Lee (2014) established a solid basis for understanding when to use grounded theory rather than qualitative content analysis. Cho and Lee's (2014) literature review serves as a good guide on how this current study will be conducted.

Downey (2018) conducted a mixed methods research that explored the audit offshoring process and examined differences in performance due to work design changes to accommodate offshore engagements. The first part of Downey's (2018) research was a qualitative study that used semi-structured interviews to gather senior local audit staff and managers' perceptions about offshoring auditing activities. These interviewees were in Downey's (2018) personal contacts network. A similar methodology was used by Power and Gendron (2015) in a related study that set the foundation for Downey's (2018) study. The findings of Downey's (2018) study indicate that firms taking advantage of offshoring believe it will yield cost reduction and an around-the-clock workforce, as well as more free time for local audit staff to focus on advanced work.

The second part of Downey's (2018) study used an experimental design to test the hypotheses proposed. The dependent variable for the quantitative study was the performance of auditors comparing offshoring to non-offshoring practices (Downey, 2018). The second phase surveyed 173 participants comprised of 71 auditors and 102 students. The quantitative study portion concluded that unfinished work, considered less critical which was assigned to offshore teams was associated with poor performance (Downey, 2018). Downey (2018) also developed a coding scheme which was revised several times based on data collected through the interviews. This approach mirrors the current study's approach, which used the grounded theory to collect data and go through a series of coding schemes to refine the themes about IS audit effects on efficiency and labor costs.

Larsen, Manning, and Pedersen (2013) investigated hidden costs associated with service offshoring and concluded that most firms do not recognize the need for process redesign to engage offshore teams, resulting in hidden costs. Larsen, Manning, and Pedersen's (2013) findings stressed the importance of organizational design and experience in handling enterprise complexity driven by outsourcing. In the case of analytical procedures associated with work assigned to offshore teams, the use of data analytics would help firms save labor costs while achieving enhanced audit quality, improved audit effectiveness, and improved client service (Larsen, Manning, and Pedersen, 2013). Sirois and Savovska (2018) concurred with Larsen, Manning, and Pedersen (2013) on the savings guaranteed from leveraging data analytics with offshore teams to reap combined benefits.

Payne and Curtis (2017) conducted a quantitative study that explored factors associated with auditors' intention to learn non-mandatory technologies in their practice. Payne and Curtis (2017) investigated the causes of resistance to new technology and found a major cause is lack of knowledge of the value of technology in auditing. They concluded that busy-season pressure lowers interest in technology training offered during peak hours. However, proper timing of training for auditors would promote an increase in knowledge of IS audit efficiency and cost benefits to audit projects. Although Payne and Curtis's (2017) work did not focus on a specific technology such as data analytics, it brought into focus some of the current issues and debates about the IS audit practice as far as new technology adoption. The study leveraged the technology acceptance theory (TAM) and its applicability in auditing based on Mahzan and Lymer's (2014) study. Payne and Curtis' (2017) study investigated the timing of technology training for auditors as a potential remedy for resistance to optional technology use and training. Kotb and Allam (2015) concurred with Payne and Curtis (2017) that the main constraints of using audit technology in the audit practice stem from lack of IT training.

Payne and Curtis (2017) also claim the pressures of repetitive manual audit work and lack of education on the capabilities of available technologies form the two biggest obstacles to acceptance by auditors. Payne and Curtis (2017) surveyed 114 auditors from many accounting firms of all sizes. The survey was split into two workstreams: the first used an online questionanire instrument targeted to a select number of accounting firms that had consented to a survey request. The second survey was a printed version of the same instrument administered to auditors attending a national training class for their company. The data collection method used by Payne and Curtis (2017) has similar attributes to the one proposed in this research, which targeted 27 experienced auditors of ISACA membership with an online instrument.

In support of Payne and Curtis's (2017) research, Lowe, Bierstaker, Janvrin, & Jenkins (2018) contended there remains a big divide between perceived importance and the actual use of audit technologies in practice. Lowe, Bierstaker, Janvrin, & Jenkins (2018) investigated the extend to which auditors from the Big 4 firms use and assess perceived criticallity of information technology in audits. They found Big 4 auditors were not significantly likely to adopt IT than auditors from other firms.

Hall, Higson, Pierce, Price, and Skousen (2012) conducted three quantitative research experiments that established differences between haphazard sampling and random sampling. Haphazard sampling is a non-statistical technique used in place of random sampling. The key findings were that without remediating the use of haphazard sampling, the approach is likely to expose auditors to legal and regulatory risk in addition to being required to repeat audits. This haphazard sampling selection bias could be eliminated by using one of two data analytics techniques; k-fold cross-validation or machine learning using random sampling with a large number of training samples (Alkoot & Kittler, 2001; Etikan, Musa, & Alkassim, 2016; Ramadevi, Rani, & Lavanya, 2015).

Hall et al. (2012) concluded that a data analytics approach to random sampling ensures better efficiency and minimizes bias, which could be a more efficient way to achieve effort minimization and data diversification. Hall et al. (2012) used a sample of 22 pages of accounts receivable transactions containing 792 customer accounts along with 26 pages of 1,404 inventory items. The dataset was split between three quantitative experiments in which participants selected haphazard samples from the available datasets. One limitation of this study is it focused entirely on traditional sampling methods without considering available data analytics sampling methods such as k-fold cross validation (Grimm, Mazza, & Davoudzadeh, 2017; Triba et al., 2015). A data analytics approach such as data mining could have helped analyze the entire dataset in anomaly detection as it is already widely applied to fraud detection in the financial industry (Buczak & Guven, 2016; Erfani, Rajasegarar, Karunasekera, & Leckie, 2016). The quantitative study by Hall et al. (2012) lacked a better theory to study the sample selection biases. However, their effort helped to create a foundation for the use of data analytics in IS auditing to sanitize the process and minimize labor costs.

Bergquist and Elofsson (2016) conducted a qualitative study that explored the effects and implications of collaboration between financial auditors and IT auditors. This study found that collaboration enabled a more effective audit process. Bergquist and Elofsson (2016) used semi-structured interviews to elicit responses from 14 participants – 11 financial auditors and three IT auditors employed by the “Big 4” companies in Sweden.

Although Bergquist and Elofsson (2016) did not focus on the use of data analytics in IS auditing, they sought to provide an understanding of the current status of the audit profession. Their research also investigated the need to lower labor costs on audit engagements and raised the issue of efficiency. The study shares the same approachas this current research in that it used open-ended questions, enabling participants to freely provide their opinions. A similar approach was also used in a few related studies such as Bell, Bryman, and Harley (2018, p.11) and Saunders, Lewis, and Thornhill (2009, p.348).

Bergquist and Elofsson (2016) employed an inductive approach to epistemological professional theory to investigate perceptions of auditors they interviewed. The study aligns well with this current qualitative study. The current study focuses more on developing a theory to understand how the use of data analytics in the IS audit process can help to minimize labor cost and improve efficiency. A critique of Bergquist and Elofsson’s (2016) study is their separation of IT auditors from financial auditors, whereas business is now all driven by IT (Dai & Vasarhelyi, 2016).

Table 3 below is a summary of the literature examined that discussed theories, methods, and techniques in IS audit research. The summary captures the authors, methodology, and findings of each study.

Table 6

Summary of Theories, Methods, and Techniques in IS Audit Research

Authors	Methodology	Findings
Axelsen, Green, and Ridley (2017)	Qualitative	• Developed an explanation theory that helped define the role of IS auditor in a financial audit.
Cho and Lee (2014)	Qualitative	• Delineated the relevant research goals and rationale for choosing between grounded theory and qualitative content analysis methods. • Established a solid basis for understanding when to use grounded theory.
Downey (2018)	Mixed Methods Research	• Audit offshoring negatively affects performance. • Offshoring can create opportunities for local auditors to advance professionally by freeing up time for advanced projects. • Offshoring offers cost reduction and a 24/7 workforce. • Unfinished work that is considered less critical assigned to offshore teams is associated with poor performance.

Table 7

Summary of Theories, Methods, and Techniques in IS Audit Research Continued

Authors	Methodology	Findings
Gregor (2006)	Qualitative	• Distinguished differences between five interrelated types of theory: the theory of analyzing, the theory of explaining, the theory for predicting, the theory for explaining and predicting, and the theory for design and action
Larsen, Manning, and Pedersen (2013)	Quantitative	• Emphasized the need for process redesign to engage IS audit offshore teams.
Payne and Curtis (2017)	Quantitative	• Busy-season pressures are of more concern to auditors than technology training. • Recommends needed to train during off-peak periods.
Hall, Higson, Pierce, Price, and Skousen (2012)	Quantitative	• Without remediating the use of haphazard sampling auditors exposed to legal and regulatory risk in addition to repeating audits. • Estimation consequences of selection biases prevalent in Haphazard sampling.
Bergquist and Elofsson (2016)	Qualitative	• Collaboration between financial auditors and IT auditors enabled a more effective audit process.

Critiques of Data Analytics in IS Audit

There is a plethora of recent literature focusing on increased productivity, performance improvement and cost reduction when deploying data analytics, but little attention is given to privacy rights and ethical implications of its usage (Asadi Someh, Breidbach, Davern, & Shanks, 2016). Holt, Lang, and Sutton (2016) provided a unique view of the ethical issues of monitoring and auditing employees in workplace environments. In their quantitative study, Holt et al. (2016) employed the theory of Contractarian Ethics to explore potential employee perception the effects of active monitoring of potential employee willingness to accept job offers in certain organizations. Contractarianism emerged from the belief that society will never resolve deep moral disagreements (Luetge, Armbrüster, & Müller, 2016). Arguments about privacy violations arising from data analytics usage in the IS audit process have found a defense in the Contractarian Theory and the arguments may slow its adoption (Holt, Lang, & Sutton, 2016).

Holt et al. (2016) conducted two experiments. First investigated participants' ethical perceptions of active monitoring and the probability of someone accepting a job offer, while the second experiment examined the significance of the evidence presented to lessen raised adverse perceptions. The findings suggest evidence of active monitoring and pay are strong determinants of job acceptance and satisfaction. An apparent shortcoming of this study is that it generalizes potential employees without focusing on the specific job types. Holt et al.'s (2016) research was a quantitative causal study that used data from a seven-point Likert Scale survey (Vagias, 2006). The instrument in this dissertation also leveraged the seven-point Likert Scale approach with semi-structured open-ended questions.

Che, Langli, and Svanström (2017) examined the effects of formal education, continuing professional education, and professional experience on audit effort and audit quality. Che et al.'s (2017) quantitative study utilized a sample of 1,738 auditors with 178,770 client-year observations from 2006 through 2010. The study found a positive correlation between audit effort and continuing professional education but no correlation between the use of data analytics and audit quality. Che et al. (2017) established that knowledge and effort are significant determinants of audit quality. A critical limitation of Che et al.'s (2017) study was the insufficient discussion of the theoretical framework employed in the study.

Some earlier studies have disputed the importance and value of technology in auditing. DeAngelo (1981) argued that audit quality is a function of audit firm size regardless of the level of technological capability. DeAngelo's (1981) claim seems to contradict the assumption that knowledge and experience in data analytics improve the IS audit process' efficiency and cost minimization. Contrary to DeAngelo's dispute of the significance of technology to audit quality, regardless of audit firm size, the modern audit practice is engaging technical specialists to enhance quality (Bauer & Estep, 2017). The industry is investigating ways to leverage advanced analytics in auditing and IS auditing specifically, but fear of the unknown seems to be impeding progress (Alles, 2015). Data analytic concerns in the audit community today entail competencies needed by auditors in big data environments, the need for the change of auditing standards, and the applicability of modern analytics in auditing (Vasarhelyi, Kogan, & Tuttle, 2015).

Table 8

Summary of Critiques of Data Analytics in IS Audit

Authors	**Methodology**	**Findings**

Holt, Lang, and Sutton (2016)	Quantitative Causal	• Evidence of active monitoring and pay are strong determinants of job acceptance and satisfaction.
Che, Langli, and Svanström (2017)	Quantitative	• Auditors with graduate degrees exert more effort compared to those with undergraduate degrees. • Continuing professional education has a significant positive impact on audit quality.
DeAngelo (1981)	Qualitative	• Audit firm size gives larger audit firms advantages • Audit quality is independent of technological capabilities

Chapter Conclusion

Existing literature on the use of data analytics in IS auditing has demonstrated that the audit profession is lagging behind. There is not much literature that has thus far focused solely on the use of data analytics in IS auditing to improve efficiency and lower labor costs. Much of the recent research has been focused on the impact of big data and advanced technologies on the audit practice within the context of financial auditing (Appelbaum et al., 2017; Castellano, Presti, & Gobbo, 2017; Vasarhelyi, Kogan, & Tuttle, 2015). Porte et al. (2018) found that the three most popular audit research themes were audit market, financial audit report statement users, and corporate governance. Audit education, audit sampling, and audit procedures were among the least studied themes in audit research, which is surprising considering the advances in technology that future auditors will need (Porte et al., 2018).

Much of the literature that favors the use of data analytics in auditing for improved efficiency and minimization of labor costs highlighted the ability to test 100 percent of the enterprise datasets quickly (Downey, 2018; Earley, 2015; Gonzalez & Hoffman, 2018). Sirois and Savovska (2018) set out to investigate the benefits of data analytics on audit quality and their findings reported improved client service and increased efficiency. Advanced data analytics techniques such as deep learning and text mining are starting to emerge as future audit research themes (Castellano, Presti,& Gobbo, 2017).

Chapter Summary

According to Singh et al. (2017), data analytics enable exhaustive testing of data, yielding faster audits and cost savings for firms. In a related study that investigated data analytics preprocessing methods, Perols et al. (2017) found that use of data analytics in IS auditing improved fraud prediction performance by 10% compared to current techniques, the ability of the Securities and Exchange Commission (SEC) to detect fraudulent filings, and improved audit firms’ client portfolio decision-making.

Chapter 3 addresses the appropriateness of the selected research methodology for this qualitative study. It also provides a detailed description of the data collection exercise from an online survey instrument. It further explores the grounded theory approach for coding data in developing a new theory in line with the literature discussed above.

CHAPTER 3: METHOD

This chapter discusses the research method used in the study as well as design appropriateness. It details the population used in this study and the rationale for the nature and composition of the population. The chapter explores the pilot study sampling, data collection procedures, and the ethical considerations of the approach. It also presents the methods used in internal and external validity and data analysis.

Research Method and Design Appropriateness

This is a qualitative study that employed the grounded theory to analyze data collected through an online survey. The purpose of this qualitative study was to understand how the use of data analytics in the IS audit process could lower overall labor costs and improve efficiency. An anonymous data collection online questionnaire contained semi-structured open-ended questions to elicit auditor perceptions on their use of data analytics in the audit process. The open-ended questions encouraged participants to freely express their feelings without being guided into giving structured responses that fit the researcher's specific needs (Belgrave, 2014; Belgrave & Seide, 2018; Charmaz, 2015). This approach was adopted from Belgrave and Seide's (2018) handbook on the principles of the grounded theory and open-ended semi-structured questionnaires.

The grounded theory approach establishes a framework allowing constant comparative analysis as successive data is collected and coded (Rivers, 2018). The grounded theory has its foundations in social sciences, where it has competed with phenomenology, ethnography, case study, and biography theories (Creswell & Creswell, 2017). Grounded theory is distinguished by a two-step approach which starts with concept generation followed by explanatory theory generation (Charmaz, 2014), similar to the approach described by Lindlof and Taylor (2017) and Thornberg and Charmaz (2014). This study's methodology map is described in Appendix C.

Research Questions

The general research question was: “How can the use of data analytics in information systems (IS) auditing improve the audit process and minimize costs?” This general question breaks down into the following related questions:

RQ1: How can the application of data analytics in information systems (IS) audit improve the IS audit process?

The survey questions below were designed to elicit responses from participants for research question RQ1.

Survey Questions, RQ1

1. Thinking back on your career in auditing, what can be done in the IS audit practice to help audit teams accomplish more tasks with fewer resources?
2. What has been the typical size of your audit team(s) on different projects?
3. What types of data analysis do you conduct on your audits?
4. What percentage of your work time do you spend on data analysis?
5. How could you, your firm, or your client(s) benefit from engaging data analysts or data scientists on your audit projects?

RQ2: Can the cost of labor be lowered in information systems (IS) audit by utilizing data analytics?

The survey questions below sought to determine auditor perceptions cost involved in specialist involvement on projects.

Survey Questions, RQ2

1. What percentage of your IS audit project costs is typically allocated to hiring analysis specialists?
2. What can be done in the IS audit process to minimize the number of specialists hired?
3. How does engaging specialists affect project cost?
4. How could in-house predictive analytics improve IS auditing?

RQ3: How can the use of a data analytics framework improve IS auditing?

The survey questions below were designed to gather data to explore research question RQ3.

Survey Questions, RQ3

1. What changes, if any, should be made to the information technology assurance framework (ITAF) to pave the way for the use of data analytics in the IS audit process?
2. In what ways could a data analytics framework improve the planning and review of audits?
3. How could the introduction of a data analytics framework address SAS No. 94 requirements?
4. How could the use of data analytics in the IS audit process affect compliance with SAS No. 56?

RQ1 probed perceptions of IS auditors on the value of data analytics in streamlining the IS audit process. The question explored the composition of IS audit teams concerning staffing sizes, the effort required for data analysis tasks, and the specialist skillsets required to provide full continuous assurance (DeAngelo, 1981; Hux, 2017; Sun, 2018; Sun & Vasarhelyi, 2018). Hux (2017) argued that the use of specialists in the IS audit process positively impacts audit quality but it may increase costs.

RQ2 sought to investigate ways in which data analytics could be used in the IS audit practice to lower labor costs associated with carrying out audits (Pathak et al., 2005; Pong & Whittington, 1994). Early research conducted by Pong and Whittington (1994) proposed an audit model that determines fees based on client firm size-based sales and assets of the auditee. RQ2 explored the assumption that audit automation through data analytics could help lower labor cost.

RQ3 raised the need for a framework that can guide the use of data analytics in IS audit engagements. Wang and Cuthbertson (2014) argued there is a need for a framework to guide data analytics usage in the IS audit process. A proposal for a predictive audit framework made by Kuenkaikaew and Vasarhelyi (2013) contended that the traditional audit practice is at best backward-looking compared to the promise of predictive auditing that can provide preventive measures. An IS audit data analytics framework would strengthen the organizational control environment if integrated into overall enterprise governance (Mangalaraj et al., 2014).

Population, Sampling, and Data Collection Procedures and Rationale

An online survey was posted on the LinkedIn group of auditors who are members of the ISACA with the hope of gathering a minimum of 25 responses. The semi-structured online survey approach was best suited to the target participants, since it was challenging to carry out in-person interviews as most auditors' travel. A similar approach was used in a study that examined the design and evaluation of student-focused eLearning (Bentley, Selassie, & Shegunshi, 2012). The difference with this current study was that Bentley et al. (2012) used a longitudinal semi-structured survey which collected data over time. The research design for this study used a cross-sectional survey design that collects data at a point in time (Creswell & Creswell, 2017). The survey instrument collected data on the IS audit process efficiency, audit labor costs, and the need for an audit data analytics framework.

A pilot study was necessary to provide the researcher with data to form an assessment of steps to be followed in the main study. In addition, the pilot study provided data on the management of time and budget, human bias, and data challenges (Thabane et al., 2010). The pilot study elicited responses from three IS auditors, all currently certified information systems auditors (CISA) at ISACA. Finally, the pilot study data collected was used to improve the survey instrument to ensure valid responses (Chenail, 2011). The results of the pilot study are discussed in detail in chapter 4.

Population

The general population of audit professionals includes designated IS auditors, internal auditors, financial auditors, and external auditors, as all of whom perform some form of IS auditing. The chosen ISACA organization provides professional education, networking, and training to members. This ensured that the target population for this study included individuals who were knowledgeable about the subject of this study (ISACA, 2018). The ISACA population was primarily composed of ISACA-certified audit and information systems risk professionals who met certification requirements stipulating a minimum of four-years' experience in auditing (Stafford et al., 2018). By design, the target population included only adult participants, which supports ethical considerations on consent expectation (CITI, 2018).

Sampling

The target population, also referred to as the sampling frame (Creswell & Creswell, 2017), only included adult ISACA Certified members who were employed as auditors. Grounded theory-based studies select participants who are the most qualified to provide valuable insights about the topic under study (Sbaraini, Carter, Evans, & Blinkhorn, 2011). The participation invitation process was initiated through ISACA member support communication channels, which pointed the researcher to the LinkedIn group. The invitation process followed a modified approach of Creswell and Creswell's (2017) to solicit participation; the target population existed in a LinkedIn group consisting of thousands of members. The survey questions included three demographic questions to confirm the adult status, to comply with CITI's (2018) human subjects research considerations, the appropriate certification status with ISACA, and the required audit experience to ensure validity of the study. The survey questions did not request demographic statistics which could influence participant responses.

According to Morse (2000), grounded theory studies of unstructured survey questions may need 20 to 30 participants. The process of soliciting volunteers from the entire population of ISACA members made it likely that the target number of surveys completed would meet the minimum of 25 survey responses needed for the study. The reason for submitting the survey to the entire population of ISACA was to guard against bias and low response rate. Not all participants expressed their perspective on the questions well. Because the researcher did not incentivize participation, the survey data collection allowed for the risk of low participation, therefore the survey was submitted to all eligible members of ISACA in the LinkedIn group.

As each completed survey was examined in order of receipt, themes emerged. Initial survey responses informed the direction of further survey response selection to achieve saturation by filling gaps in the initial data (Davis, 2014). The pilot study employed theoretical sampling by surveying three participants who have IS audit experience and hold ISACA certifications. The sample size estimation for this study took into consideration a number of factors including the scope of the study, the quality of the data, the number of questions each participant had to answer, and the grounded theory approach study design (Morse, 2000). Given that many surveys struggle low response rates, the researcher chose to target the entire population of the ISACA membership present in the LinkedIn group. According to Bryman and Bell (2011, p.235) a 37% survey response rate is typically maximum.

Sampling in grounded theory is generally driven by emerging categories and theories from constant comparative analysis and theoretical sampling (Goulding, 2002). The survey was designed to remain open to the target population until data saturation was reached. In narrow-focused qualitative studies, theme saturation is usually achieved before exhausting the sample of survey responses from solicited participants (Miles, Huberman, Huberman, & Huberman, 1994, p.69). The concept of data saturation in qualitative research – specifically when applied to the grounded theory approach – refers to a point in data collection when fresh data no longer produce new insights (Charmaz & Belgrave, 2012; Fusch & Ness, 2015).

Data Collection

Collecting data from the participants is achieved by deploying a semi-structured cross-sectional online survey (Agius & Wilkinson, 2014; Bell, Bryman, & Harley, 2018, p.11). Agius and Wilkinson (2014) collected students' and teachers' views via written feedback using semi-structured cross-sectional online surveys which enabled accumalation of sufficient quality data. Online surveys offer fast and low cost data collection and are mostly credited with eliminating interviewer effects which negatively impact response quality (Duffy, Smith, Terhanian, & Bremer, 2005). Online surveys are also considered visual, interactive, and flexible (Szolnoki & Hoffmann, 2013). These attributes are suitable for busy and educated people who may not be available for telephone or face-to-face interviews (Szolnoki & Hoffmann, 2013). Online survey instruments also offer some added convenience to participants because they can select the best time of the day and place to complete the survey, which may increase the number of volunteers (Shelton, 2014).

The semi-structured cross-sectional online survey was selected for this study due to two primary considerations. First, semi-structured surveys offer a chance for participants to freely relay their perceptions and experiences and encourage them to answer more fully. Second, a semi-structured survey provides a quick method of collecting varied experiences from a variety of projects, client sizes, industries, and types of employment: either consulting services or full-time direct employment. In general, semi-structured survey data collections are well suited to qualitative research since the objective is to probe perceptions and opinions of respondents with no need for statistical analysis (Jansen, 2010; Tran, Porcher, Falissard, & Ravaud, 2016). Cross-sectional survey was relevant in this study because it is focused on understanding the state of the IS audit practice regarding the use of data analytics for efficiency and cost improvements.

Open-ended questions in surveys fall into three categories: list of items, numerical entry, and descriptive open-ended questions (Dillman, Smyth, & Christian, 2014). The use of open-ended survey questions enables the collection of detailed responses from auditors regarding the use of data analytics (Jansen, 2010). Open-ended survey questions enable a comprehensive description of all facets of a topic and data saturation (Tran, Porcher, Tran, & Ravaud, 2017). In this study, the researcher used open-ended questions to enable respondents to provide rich and detailed information regarding the use of data analytics in IS audit practice. A similar approach was used by Tourangeau, Kreuter, and Eckman (2015, p.33). Descriptive open-ended questions are less frequently used in research because of the need for time-consuming data cleaning and coding; however, their advantage is that they provide high-quality data (Chaudhary & Israel, 2016).

A detailed survey design discussion is provided in the instrumentation section below to support the validity and reliability of the method used in this study. The pilot study helped establish internal consistency of the survey questions. By categorizing themes, coding, and the constant comparative analysis of participant answers, the researcher hoped to develop a new theory that reveals the cost-effectiveness of using data analytics in IS audit (Creswell & Creswell, 2017; Tran et al., 2016).

In this study, the researcher's target was to use survey data responses from the first 25 to 30 complete surveys based on a first-come-first picked approach. The survey was designed to be closed once the target number of good and complete responses was received. According to Creswell and Poth (2018, p.157), there is no best answer as to how many participants provide data saturation, but rough estimates for the grounded theory are between 20 and 30 participants. Data saturation for this study will be reached when further coding does not produce any more information or concepts. Given the industry and diverse geographic locations of survey participants, getting to a point where no more new information is elcited in responses would be a sign of saturation. Tran et al., (2016) summarized data saturation as an elastic notion where the number of participants depends on the purpose of the study and the analytical level desired.

Instrumentation

The data collection instrument for this study was an online survey comprised of semi-structured open-ended questions to collect qualitative data (Smyth, Dillman, Christian, & McBride, 2009). The survey questions are designed to probe perceptions that address the stated goals. The survey instrument had three sets of questions. (See Appendix B for the survey instrument design.)

The first set established informed consent of participants. The second set established participants' age range (18 or over) to support consent considerations and to confirm participants' ISACA membership, certification, experience, and job title to support the validity of the study. The third set of questions was used to collect qualitative data for analysis. Using Chaudhary and Israel's (2016) approach, each question in the third section had an answer box sized for 250 words each with a statement saying, "Type as much as you wish." The larger box size and the motivating statement "Type as much as you wish" were intended to improve response quality (Chaudhary & Israel, 2016). In a study on open-ended questions in online surveys, Smyth et al. (2009) found that open-ended questions that included a motivating statement had a larger number of words in their responses compared to those without motivating statements.

Validity: Internal and External

In qualitative studies, validity and consistency refer to credibility, transferability, dependability, and confirmability of data collection instruments and study results (Simon & Goes, 2016). Validity is a determinant of the accuracy of the findings from the standpoint of the researcher, the participant, or the recipients of the study (Creswell, 2003, p. 196). The online survey described in the instrumentation section inherits much of its structure from Shelton's (2014) instrument but had only open-ended questions for the qualitative data collection. Although Shelton's (2014) survey instrument was designed to collect both ordinal and descriptive data, the structure and validation framework was similar to the qualitative section. Since this study was a completely qualitative study, this section sought to establish the validity of the survey instrument before conducting the main study (Fink, 2016). The researcher adopted Fink's (2016) step-by-step approach on how to conduct a survey with a validated instrument.

The pilot study utilized the survey to establish reliability and validity of the online instrument (Creswell & Creswell, 2017; Fink, 2016). The online survey instrument also followed the open-ended online survey instrument design recommended by Fink (2016) to conform to survey validity expectations. Fink's (2016) approach involved drafting open-ended questions that give participants the ability to respond freely based on the context of the query. Researchers carrying out similar qualitative research studies have used online surveys (Burg et al., 2015; Esuli & Sebastiani, 2010; Reja, Manfreda, Hlebec, & Vehovar, 2003; Schierholz, 2014).

Survey Reliability

Survey reliability was established by administering the online survey to three pilot participants before conducting a full-scale study survey. The initial online survey administered to pilot study participants contained an additional section with questions about the nature and clarity of the questions as adopted by Leon, Davis, and Kraemer (2011). The feedback from the pilot study was used to make layout and question clarity changes as needed before launching the final online data collection. Two of the pilot participants were researchers with expertise in survey development to ensure the questions were correctly formulated and did not introduce bias. Appendix B shows the final survey including the pilot study questions.

Internal Validity

In qualitative research, internal validity is also known as credibility (Creswell & Creswell, 2017). According to Guba (1981, p. 84) credibility is dependent on the degree to which the participants' perceptions match the researcher's interpretation. In this study, credibility will be assured through member checks; the researcher will review summaries of participants responses with two pilot study participants (who are researchers in audit) to validate accuracy. Member checks involves continuous testing of the researcher's data, analytic groups, interpretation, and conclusions (Krefting, 1991). Response uniformity in participants' answers will be used as confirmation of instrument validity and response verity (Szul, Bompas, Sumner, & Zhang, 2019). The reliability and validity of surveys are products of definitions and models that are grounded in theory (Fink, 2016). Since the participants in this study were auditors, the assumption was that they are experienced in writing descriptive reports of their work. Continuous member checking will be adopted to help establish reliability of the instrument and participant answers (Candela, 2019). According to Iivari (2018) member checking is a technique aimed at increasing trustworthiness and credibility of research. The research will leverage member checking to increase the fidelity of the study. Limiting the targeted population to only ISACA certified members on LinkedIn ensured adequate quality control of the survey process. Therefore, they are ideal candidates to provide precise and accurate perceptions of the use of data analytics in IS auditing. Auditing requires analytic review of audit evidence, and this also made using auditor participants the best approach to collect valid data (Lenz & Hahn, 2015).

Participant selection bias could skew the sample attributes relative to the population of potential participants (Hatch et al., 2016). In this study, the invitation to participate was open to all members of ISACA, thereby preventing selection bias in terms of target population. Given that most auditors travel around their region as part of their work, geographic bias is minimal (Yustina & Putri, 2017). The survey was designed to prohibit resubmission of survey responses, so each participant was allowed to only complete the survey once to avoid repeated participation. Participants did not have access to the responses of others and were not able to change a submission once saved. The survey was not further changed after pilot survey feedback changes, since any changes to the instrument during the administration of the survey could affect the internal validity of the data collected (Fink, 2016; Fraenkel, Wallen, & Hyun, 2011, p.165).

External Validity

External validity (sometimes referred to as transferability) concerns can originate from participant selection methods. External validity is concerned with how well the study guarantees related research will produce close to similar results (Guba, 1981, p.83). The usefulness of any survey research results is predicated on the absence of external validity issues such as change in context producing completely different outcomes (Huebschmann, Leavitt, & Glasgow, 2019). This current study's design ensured transferability by encouraging participants to respond with detailed description (thick descriptions) of their perceptions on survey questions. Thick description in this study was ensured by allowing participants to provide deep, dense, and detailed accounts of their perceptions about the subject of inquiry (Ahmad-Tajuddin, 2014). In this study, participants were considered qualified respondents based on their work experience, education, certifications, and ISACA membership. The survey focused on auditors' perceptions and experiences without involving any form of interaction that could threaten the external validity of the survey (King & He, 2005). Most commonly, external validity is a significant issue in quantitative research studies where the results of the study are expected to be generalizable (Johnson, 1997). Typically, generalizability is not the aim of qualitative research (Leung, 2015). In the current qualitative study, external validity is given strong consideration because the goals of the study include developing a theory grounded in the data, with the hope that the new theory would find wider acceptance and use.

Dependability

Dependability in qualitative research corresponds to the concept of reliability in quantitative research, affirming that findings are consistent and could be repeated (Lincoln & Guba, 1985, p. 300). It seeks to establish the consistency of the findings through inspection of raw data and data reduction products (Gunawan, 2015). To establish dependability in this study, the researcher will engage DataSense LLC, to help with NVIVO coding and inquiry audit. The researcher collected all the process memos and maintained a paper trail to ensure a thorough audit of the entire study.

Confirmability

Confirmability measures the degree of neutrality. It assesses the extent to which the findings of the study are influenced by participants' responses as opposed to being shaped by researcher bias (Lincoln & Guba, 1985). The researcher will use inquiry audit to establish confirmability in this study. The audit trail for the study will include raw data, notes from coding, theoretical notes, pilot study notes, and changes made.

Data Analysis

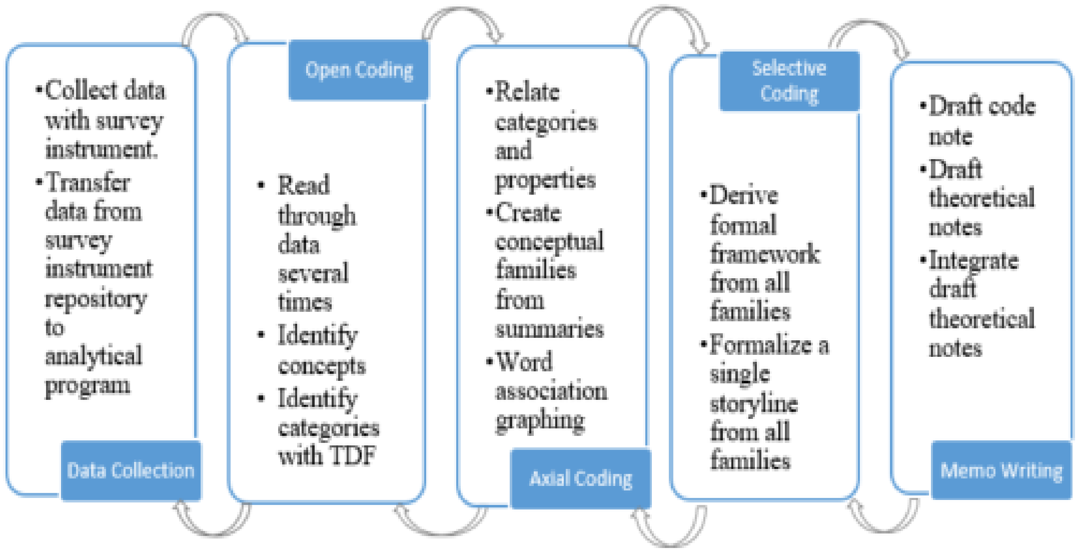
Data collection for this qualitative study will be captured from narrative survey question responses. In a qualitative study with semi-structured, open-ended research questions intended to generate a theory grounded in the collected data, a coding theme extraction method is suitable (Charmaz, 2014; Charmaz, 2015). This section describes the steps for analyzing the survey responses to build a theory grounded in these responses. Analysis of the survey responses followed the constant comparison process, which alternates between collecting data and analyzing it (Foley & Timonen, 2015).

Grounded theory was used to guide the study method through concept coding and identifying relationships between the concepts. The four phases that are leveraged in the grounded theory-based analysis are open coding, axial coding, selective coding, and memo note writing (Weller et al., 2018). Data collection and analysis occur concurrently in grounded theory, and the process of discovering themes is referred to as open coding (Charmaz, 2015; Thornberg & Charmaz, 2014). In the first stage of coding, noting repetition of words or phrases is the easiest way to identify themes from a corpus of data (Ryan &Bernard, 2000). Constant comparative analysis is structured into four phases: "(1) comparing incidents applicable to each category, (2) integrating categories and their properties, (3) delimiting the theory, and (4) writing the theory" (Glaser & Strauss, 2017).

Figure 2 shows the planned steps in concurrent data collection and analysis with a feedback loop to support constant comparison and theoretical sampling (Charmaz & Belgrave, 2007; Charmaz & Belgrave, 2012). Constant comparative analysis involves continuous data collection, coding, and theoretical sampling to enable theory generation from the data collected (Kolb, 2012). The researcher used a table form based on the original dataset format from the survey instrument repository as in Appendix B, "Survey Instrument." Coding columns were appended to the original data table to allow for an easier continuation of analysis. The actual analysis of the collected data leveraged constant comparison and theoretical sampling as described by Corbin and Strauss (2008). A preliminary survey that collected pilot study data from three preselected participants will help to establish validity of the instrument and created initial codes (Khorsan & Crawford, 2014). The grounded theory analysis process proposed in this chapter use a series of coding activities to enhance internal validity (Pandit, 1996).

The process of identifying themes from the collected survey data responses will proceed as described by Charmaz (2014). The initial coding task will follow line-by-line coding, naming each line of the collected data. Line-by-line labeling of collected data provides a comprehensive analysis of detailed data and rigorous analysis of participants' responses to ensure theoretical saturation (Glaser, 1978). To support initial coding, text mining and natural language processing (NLP) techniques will be used to automate theme categorization and analysis (Nuzzo et al., 2010). Coding will primarily be conducted using NVIVO.

Figure 2. Planned Steps in Grounded Theory Analysis Process



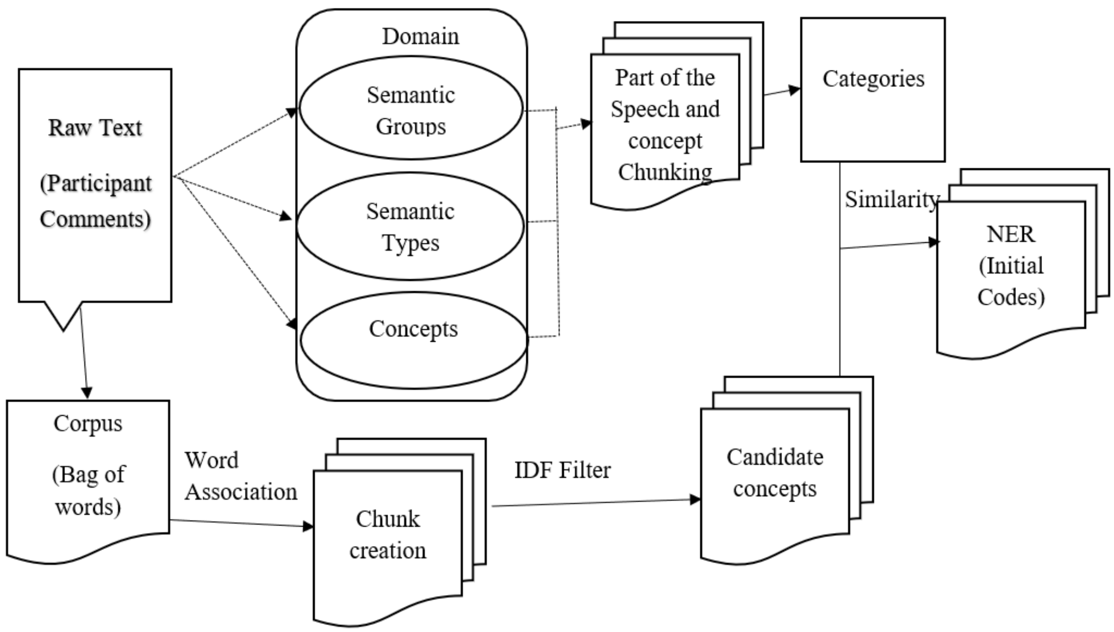
Note: Derived from (Burden & Roodt, 2007), Figure 1: Implementing the grounded theory process.

NVIVO is a qualitative research software package for text-based data analysis. NLP is a component of computer science that uses computational techniques to learn, understand, and produce human language content (Hirschberg & Manning, 2015). It involves low-level language understanding and processing tasks. Different algorithms for text mining and natural language processing were explored to improve the accuracy of categorizing themes (Zareapoor & Seeja, 2015). Text mining involves detecting and extracting information from unstructured data sources (Salloum, Al-Emran, Monem, & Shaalan, 2018).

The researcher will explore concept extraction also referred to as named entity recognition (NER), an NLP process of grouping words and phrases into surface and semantic similar groups (Poria, Hussain, & Cambria, 2018). Extracted concepts will help to establish initial themes through sentiment analysis, word association, and colocations of participant comments. NER is a subset of NLP but can be an important task in this study where it can help with classification of participants comments. The researcher intends to explore Apache OpenNLP Chunker to extract noun phrases from participants comments based corpus (Zhang & Elhadad, 2013). Apache OpenNLP is a machine learning library for computing natural language text. A corpus is a bag of words, extracted from the survey plain text responses. Participant comments for each survey question will be fed into OpenNLP model for sentiment analysis and word association. Concept extraction results will be triangulated with the grounded theory NVIVO based coding shown in figure 2 above.

Raw text from participant comments for each survey question is processed into two different streams as depicted in figure 3 below; the first breaks the response into a bag of terms (corpus) and the second extract concepts, semantic groups, and semantic types. Terms in the corpus are further computed for word associations to generate phrases to help formulate candidate concepts for themes. Word associations are a correlational analysis computing the percentage of times when certain keywords are associated with other words. After correlation computations the researcher will use inverse document frequency (IDF) which will calculate reverse word pair relationships. The second stream will use term frequency-inverse document frequency (TF-IDF) weights to refine and enrich word vector computation by adding noun phrase chunks from the raw text. Chunking is a process of picking up individual words from sentences grouping them into phrases (Banjade, Maharjan, Niraula, & Rus, 2016). In this study the resultant chunks are the initial code which are triangulated with NVIVO output.

Figure 3. Concept Extraction with Text mining



Note: Derived from (Zhang & Elhadad, 2013), Figure 1: Overall approach to unsupervised biomedical named entity recognition.

Organization and Clarity

The data analysis approach will follow Burden and Roodt's (2007) inductive roadmap for applying grounded theory to ensure data saturation. Once initial data has been received, open coding begins with concept identification by breaking the data into discrete parts to enable constant comparative analysis. Part of the initial analysis of the data will incorporate text analysis in R statistical software to analyze term-document frequency and inverse term-document frequency analysis (TDF, ITDF) to enable faster concept labeling.

Chapter Summary

The qualitative methodology for this study is designed to follow data collection and analysis which addressed the three research questions raised in this study. The grounded theory-based approach is focused on eliciting concepts and themes from IS audit practitioners to establish an understanding of how the use of data analytics in the audit process would lower labor cost and improve efficiency. The use of semi-structured open-ended survey questions encourages participants to freely express their feelings without being guided by any preconceived bias on the part of the researcher (Belgrave, 2014; Belgrave & Seide, 2018; Charmaz, 2015). The actual analysis of the data collected will leverage constant comparison and theoretical sampling as described by Corbin and Strauss (2008). A preliminary survey to collect pilot study data from three preselected participants will help to ensure the validity and reliability of the survey instrument (Khorsan & Crawford, 2014). The grounded theory analysis process proposed in this chapter will use a series of coding activities to enhance internal validity (Pandit, 1996).

Chapter 4 provides the results of the study and presents the conceptual data derived from the grounded theory-based qualitative analysis process.

CHAPTER 4: RESULTS

The purpose of this qualitative research was to understand how the use of data analytics in the IS audit process can help to minimize labor costs and improve efficiency. This chapter presents the results of the pilot study, the data collection and analysis, and the detailed research design employed in this study mirroring the methodology map referenced in Appendix C (p.207). Chapter 4 also delineates through the method used to arrive at the findings. This study addressed the following research questions:

RQ1: How can the application of data analytics in information systems (IS) audit improve the IS audit process?

RQ2: Can the cost of labor be lowered in information systems (IS) audit by utilizing data analytics?

RQ3: How could the use of a data analytics framework improve IS auditing?

The details of the instrument validation, pilot study, and an overview of the data are discussed in the remainder of this chapter. The chapter continues with a demonstration of the development of a theory grounded in the collected data to explain the effect of data analytics on the IS audit process efficiency and labor costs. Finally, the chapter presents the results of the constant comparative analysis as demonstrated by Foley and Timonen (2015) in accordance with the grounded theory process (Weller et al., 2018).

Pilot Study

The researcher began the study following the approval of the proposed research by the Institutional Review Board (IRB). According to Lancaster (2015), pilot studies are a smaller version of the main study meant to test the feasibility of components of the main study. The pilot study validated the survey instrument by determining whether the questions were properly formulated to obtain relevant data addressing the research questions. The pilot study was conducted over a nine-day period beginning on September 4th, 2019, using the planned data collection instrument on the secure site, https://docs.google.com/forms.

The selected pilot participants were informed of the purpose of the study, confidentiality and privacy considerations, and risks and benefits of participating. The responses from the pilot study participants regarding eligibility to participate confirmed that participants were not associated with any audit software vendor, were members of ISACA. It also established pilot participants were certified by ISACA and over 18. The pilot study ended on September 12th, following which the main study began.

Content Validation

The pilot study initiated the content validation. Three recruited pilot study participants from the ISACA membership reviewed the survey questions. One reviewer suggested including detailed descriptions of SAS. No. 56 and SAS. No.94, arguing that some participants may not be familiar with the propositions of these policies. The researcher decided to include text of the provisions of SAS. No. 56 and SAS. No.94, since both policies have been cited in some recent related studies (Goel, Garnsey, Liu, & Fisher, 2016).

Survey Validation

The pilot study was closed on September 12, 2019 with fully completed responses from 3 of the 4 invited participants. The pilot study used the same anonymity protection as the full survey, making it impossible to distinguish invitees who participated from those who did not. In support of the survey validation, the pilot study included an additional section with study feasibility questions.

One of the participants found the introductory section of the survey lengthy to read through; however, the other two participants indicated that they felt the level of detail in the introductory section was necessary. The researcher left the introductory section as originally composed to avoid issues with informed consent requirements. One pilot participant commented on the nature of the survey, mentioning that people may not be inclined to respond to the main survey because of the open-ended nature of the questions. This in fact proved to be a real problem on the main survey as there were very few responses per week, and it took seven weeks to close the main survey. See Appendix B for the survey as executed on https://docs.google.com/forms.

Participant Analysis

Participant Solicitation

The main survey opened for the data collection on September 12, 2019. The researcher submitted an invitation to ISACA member support services information team. Another message was posted on LinkedIn's ISACA social media group as shown in Appendix F. The initial plan was to target North Texas ISACA chapter members. However, to garner diversity of perspectives and experiences from across the audit practice, the researcher opened the survey to all members from the global ISACA LinkedIn group. The global ISACA membership social media group was chosen pursuant to recommendations from the board of the North Texas ISACA chapter. The board leadership for the chapter informed the researcher that there was a standing policy that forbids directly broadcasting survey solicitations to members. The social media group was established for ISACA members encompassing members holding the ISACA certifications required for survey completion. The target population including the ISACA members provided by member support and the Linkedin group had overlapping membership. At the time of the survey, ISACA had 159,000 members in 188 countries (ISACA, 2019). The challenge of using both the social media group and member support was that there was no way to determine the count of members of each group who read the posting during the time the survey was open. The ISACA LinkedIn group was the most efficient way to send invitations and reminders to a diverse population of ISACA members across the world. The study targeted a minimum of 25 fully completed surveys to meet the population recommended for grounded theory analysis. According to Creswell and Poth (2018, p.157), rough estimates for the grounded theory population are between 20 to 30 participants. They claim that there is no best answer as to how many participants provide data saturation.

Participant Timing

The researcher posted the survey announcement on Thursday, September 12, 2019 on LinkedIn through the ISACA group content moderator, Mr. Paul Smith. The daily rate of survey completion was close to 0 a week after the initial posting of the survey. Only four submissions were recorded in the first two weeks. The ISACA group moderator on Linkedin began posting bi-weekly reminders for members to assist with completing the required number of responses. There was a 1.75 daily response rate following the first reminder made on September 26th, 2019. The daily response rate improved to 2.00 then 3.75 following the second and third reminders respectively. Each bi-weekly reminder resulted in a few new survey completions as depicted in Table 5.

Table 9

Number of Completed Surveys Bi-Weekly

Posting/Reminder	Counts as of	New	Total	Eligible	Response Rate
9/12/2019	9/19/2019	4	4	2	
9/26/2019	10/3/2019	7	11	4	1.75
10/10/2019	10/17/2019	8	19	12	2.00
10/24/2019	10/26/2019	15	34	27	3.75

Data Collection Process

The researcher changed the target population for eligible participants from targeting ISACA North-Texas chapter to all ISACA membership across the world to enhance generalizability of results. Following the submission of the survey, the researcher monitored survey completion progress once a day. After consultations and approvals from the dissertation chair, the researcher proceeded with the NVIVO 12 coding and analysis.

At the end of the first reminder on October 3rd, the researcher started the iterative constant comparative selection and analysis of all fully completed survey responses. The analysis followed the planned grounded theory analysis process outlined in figure 2 (Burden & Roodt, 2007). The survey was closed on October 26th after the researcher had selected correctly completed responses from 27 participants.

Participant Analysis

The researcher posted the survey announcement on Thursday, September 12, 2019 through the ISACA LinkedIn group content moderator. Preliminary data analysis 3 weeks after the initial posting of the survey showed a low response rate. There were only 11 completed surveys submitted as of October 3rd, 2019. As of October 17, 2019, the data collected showed only 12 of the submitted surveys were from eligible participants. The remainder were from participants who are members of ISACA but who do not hold any ISACA certifications. Overall, the survey completion patterns showed a steady increase in submissions as consecutive reminders were posted, with the first two weeks registering four completions. The researcher eventually identified a total of 27 eligible submissions.

Sample Size

Among the 34 completed surveys, only 27 participants met the study's requirements for ISACA membership, certification status, adult of at least 18 years old, and non-software vendor field of employment. The survey questions were all mandatory, so incomplete attempts were not captured. The original proposal had targeted using 25 responses but the need for content saturation propelled the researcher to include all 27 valid responses.

Response Rate

Preliminary data analysis three weeks after the initial posting of the survey showed a low response to the survey. The response rate started at 4 from the first two weeks, increasing to 7 in the succeeding two weeks, 8 in the third bi-weekly analysis, and 15 completions in the final two weeks of the survey. As shown in Table 5 above, each successive reminder had 1.75, 2, and 3.75 response rate increases for first, second, and third reminder, respectively.

Method Used to Code the Survey Data

Coding process

Twenty-seven survey files in Word format were imported into NVIVO 12 qualitative software. Each line was manually read and coded with contextual content to the nodes shown in the node coding report below. Multiple subcategory nodes were created as the content was read and coding was refined within the nodes. The refinement through axial coding resulted in 13 main nodes with 159 subcategories. The final node titles are shown in Appendix G: Node listing of Coding Report. These initial codes were further refined and synthesized through both axial and theoretical coding into summarized categories. In the grounded theory approach, coding is a continuous process, it is not executed in discrete stages because of constant comparison analysis which tends to be iterative (Holton, 2010). For validation purposes, the same data was loaded into an R-based natural language processing script for topic modeling. The topics and word frequencies retrieved from the R model were compared to the initial codes retrieved from NVIVO. Word frequencies were closely related to each question analyzed. A detailed list of concept extraction-based initial coding results used to triangulate against the NVIVO coding conducted with the help of DataSense LLC is shown in Appendix G.

Coding strategy

The researcher's coding strategy provided links in the initial nodes to avoid analysis of every line of text to every node possible. The researcher also coded for context, enabling capturing of more content than might seem necessary. This allowed a faster approach providing the researcher with pre-coded context prior to final analysis. Context is especially important in order to provide meaning for qualitative analysis when reading the coding reports (Urquhart& Fernández, 2016). In order to reveal maximum context, the researcher focused on content related to the node titles extracted during initial coding. According to Kenny and Fourie (2015), there are many ways to interpret data, and coding is a subjective process; therefore, the researcher followed the grounded theory analysis process closely as outlined in figure 2 from chapter 3. In this study, categories had multiple meanings and content was coded to multiple nodes where appropriate. The researcher did not code everything everywhere to avoid a burdensome study since connections could be made throughout.

Node coding reports

Multiple node coding reports were compiled and exported from NVIVO 12 and organized into condensed reports to facilitate analysis. In this study, 172 individual node coding reports were summarized into 13 node coding reports with 159 subcategory sections within the reports. The final node coding report titles are shown below:

1. RQ1Q1. Accomplish more tasks with fewer resources
2. RQ1Q2. Typical size range audit team(s)
3. RQ1Q3. Types of DA on your audits
4. RQ1Q4. Percentage of work time on DA
5. RQ1Q5. Benefits of data analysts on audit projects
6. RQ2Q1. Percentage of audit costs hiring specialists
7. RQ2Q2. Minimize number of specialists hired
8. RQ2Q3. Specialists affect project cost
9. RQ2Q4. In-house predictive analytics improves IS auditing
10. RQ3Q1. Changes to ITAF use DA

11. RQ3Q2. DA framework improve IS auditing

12. RQ3Q3. DA framework SAS No. 94

13. RQ3Q4. DA compliance SAS No. 56

Open (Initial) Coding

The initial coding process started after the first four complete responses were downloaded from Google forms, imported into NVIVO 12, and coded as they were submitted. Initial coding involved categorizing portions of the data into phrases summarizing participants' responses (Charmaz, 2014). Once responses were imported into NVIVO 12, each line was separately read and coded into the appropriate node from the three-parent nodes. The three nodes were factors affecting audit process efficiency, audit cost, and adoption of an analytics framework. The parent nodes were derived from the three research questions. These three nodes were mapped into 13 subcategories and the resultant data was used to identify themes from participants' responses. Contextual coding was used to efficiently compile the final analysis without losing any feedback from participants. Context provides meaning to qualitative research analysis (Bengtsson, 2016). After every new batch of submitted responses following a reminder, the researcher conducted an initial coding for all new responses. With each new group of responses downloaded, the researcher conducted comparative analysis against the previously coded responses.

Axial Coding

Axial coding, the second phase, involved the creation of conceptual categories from the summaries created during open coding. According to Wiesche, Jurisch, Yetton, and Krcmar, (2017) axial coding develops a deeper knowledge of all categories to enable easier final coding. Axial coding allowed the researcher to determine the theoretical relevance of the initial codes. This second phase analysis was intertwined with the initial coding activities during each cycle of coding, even though axial coding had historically been designated as the second phase. Charmaz (2014) argued axial coding is not just a linear process but a phase with activities that iterate with the initial coding. Axial coding allowed the researcher to analyze and conceptualize the data simultaneously. Constant comparison analysis of the codes enabled the researcher to quickly reduce dimensions of codes and reveal category relationships.

Findings by Research Question

RQ1: How can the application of data analytics in information systems (IS) audit improve the IS audit process?

The researcher used the main study's survey results to address all three research questions beginning with audit process efficiency. The analysis of responses from the survey's first five questions are shown in table 6 below to address RQ1. The researcher compared the frequency of responses among the 27 fully completed responses. Figure 3 on page 90 shows the frequency responses from the survey citing use of automation-AI and data analytics as essential to accomplish more tasks with fewer resources in the IS audit process. Besides automation-AI and data analytics some respondents cited tools such as Agile as another way to accomplish more tasks with fewer resources. In question two (RQ1Q2), the inquiry into typical size of audit teams showed that most IS audit teams have fewer than 10 members. From the 27 respondents, 56% said their typical audit team has five or fewer members. The most cited types of data analytics conducted in IS audit included comparison tests for SOX, sample selection, and journal analysis which were noted in 15% of the responses for each. On the percentage of work time involving the use of data analytics, 19 of the 27 respondents concluded they spend more than 20% of their work on data analytics. Responses on the benefits of having data analysts and data scientists on IS audit projects highlighted risk-based focus, simplification of the analysis, outlier analysis, and speed analysis.

Table 6

Questionnaire for RQ1

Descending order of frequency responses based on No. of documents	**No. of Docs (27)**	**% of 27 Docs**
Survey Questions		
RQ1. Improve the IS audit process	27	100%
Survey Q1. Accomplish more tasks with fewer resources	27	100%
Automation – AI	14	52%
Data analytics	10	37%
Tools – Agile	9	33%
Planning	5	19%
Prioritizing	5	19%
Risk management	5	19%
Size of project	4	15%
Simplify audit methodology	3	11%
Training	3	11%
Aligning to budget	2	7%

Table 6

Questionnaire for RQ1 Continued

Descending order of frequency responses based on No. of documents	No. of Docs (27)	% of 27 Docs
Communication	1	4%
Hiring practices	1	4%
Survey Q2. Typical size range audit team(s)	27	100%
5 or fewer	15	56%
5 to 10	9	33%
More than 10	2	7%
N/A	1	4%
Survey Q3. Types of DA on your audits	27	100%
Comparisons - Testing (SOX, substantive, sample)	4	15%
Journal analysis	4	15%
Sample selection - populations - stratification	4	15%
Completeness	3	11%
General Ledger, AR and AP	3	11%
Trends-based past performance - outliers	3	11%
Accuracy	2	7%

Table 6

Questionnaire for RQ1 Continued

Descending order of frequency responses based on No. of documents	**No. of Docs (27)**	**% of 27 Docs**
Descriptive	2	7%
Payroll testing	2	7%
Predictive	2	7%
Purchasing to payment analysis	2	7%
Regression analysis	2	7%
Revenue line assurance	2	7%
Vendors	2	7%
Application control reviews - high risk - high value	1	4%
Bank reconciliations	1	4%
CAATTS Analysis	1	4%
Classification	1	4%
Clustering	1	4%
Contract compliance	1	4%
Data collection	1	4%
Deviation detection	1	4%
Diagnostic	1	4%
Documentation for failed controls	1	4%
Duplicate detections	1	4%
Error rates in data	1	4%

Table 6

Questionnaire for RQ1 Continued

Descending order of frequency responses based on No. of documents	**No. of Docs (27)**	**% of 27 Docs**
Integrity	1	4%
Inventory analysis	1	4%
KPI	1	4%
Link analysis	1	4%
Market	1	4%
Metrics	1	4%
N/A	1	4%
None	1	4%
Relevance	1	4%
Rule-based analysis	1	4%
Sales and production	1	4%
SoD checks	1	4%
Timeliness	1	4%
Travel and expense reporting	1	4%
Validations	1	4%
Survey Q4. Percentage of work time on DA	27	100%
Descending order of frequency responses based on No. of documents	**No. of Docs (27)**	**% of 27 Docs**
20%	7	26%
50% or more	6	22%

Table 6

Questionnaire for RQ1 Continued

Descending order of frequency responses based on No. of documents	**No. of Docs (27)**	**% of 27 Docs**
30%	5	19%
05%	3	11%
N/A or none	3	11%
40%	2	7%
10%	1	4%
Survey Q5. Benefits data analysts on audit projects	27	100%
Confirm - validate	5	19%
Hidden knowledge - data visibility	5	19%
Risk-based focus	5	19%
Analyze outliers - understand themes	4	15%
Efficiency	4	15%
Scope of work	4	15%
Speed	4	15%
Fewer resources	3	11%
Not much - unneeded	3	11%
Objective results and outcomes	3	11%
Process improvement	3	11%
Data integrity and availability	2	7%

Table 6

Questionnaire for RQ1 Continued

Descending order of frequency responses based on No. of documents	**No. of Docs (27)**	**% of 27 Docs**
Sample selection - population testing	2	7%
Audit planning	1	4%
Best for financial audits	1	4%
Continuous control monitoring	1	4%
N/A	1	4%
Reduces costs	1	4%
Use Tableau for analytics	1	4%

Open coding for RQ1 is depicted in table 7 below where the properties of the derived themes are established from examples of participants' actual words. Open coding enabled the researcher to capture perceptions of IS auditors on things that can be done to improve the IS audit process, such as use of data analytics – "Data analytics" (P22); "use data analytics to determine areas that need to be focused on more (anomalies) so that more resources are allocated to work on that" (P23); Automation AI/Data analytics – "1. Automation of key processes and related controls whenever is practical to do so. 2. Use of data analytics to analyze data and identify exceptions (if any)" (P21); Tools/Agile – "Agile auditing" (P25), "Automation. Increase the use of Robotics. Use newer and more nimble methodologies such as Agile Auditing" (P27). IS audit teams generally scale based on the number of manual repetitive activities, 24 out of the 27 respondents said on most projects their teams have 10 or fewer members. This creates a new understanding which may challenge the labor intensiveness claim (Hossain, Yazawa, & Monroe, 2017).

As shown in table 5 survey Q1, 56% of respondents said their teams are mostly made up of five or fewer members.

Table 10

Open Codes for RQ1

Open Code	**Properties**	**Examples of Participants' Words**
Automation – AI, Data Analytics, Tools/Agile	Felt artificial intelligence automation may help, Use of data analytics speed up task accomplishments	Automation of key processes and related controls Adoption of data analytics to analyze data and identify exceptions Agile Auditing
5 or fewer, 5 to 10	Most said from fewer than 5 to 10	5 or fewer 5 to 10 More than 10

Table 11

Open Codes for RQ1 Continued

Open Code	Properties	Examples of Participants' Words
20%, 50% or more, 30%	Most felt from 20% to 50%	No more than 20% of my time at present, but I need to increase that to over 50% across many types of audits.
Comparison – Testing (SOX, substantive, sample), Journal analysis, Sample selection - populations-stratification	Most mentioned Sample testing and selection Some said SOX analysis	Sample selection - populations – stratification Journal analysis Comparisons- Sample testing Trend analysis
20%, 50% or more, 30%	Most felt from 20% to 50%	No more than 20% of my time at present, but I need to increase that to over 50% across many types of audits.
Confirm – validate, Hidden knowledge – data visibility,	Most claim it reduces time to answer questions.	More objective results and outcomes. A large scope of assurance using less resources.

Risk-based focus, Analyze outliers – understand themes, Efficiency, Scope of work.	Improve evidence objectivity. Improves efficiency.	Speed of solutions, data integrity and availability improved. Data Analytics gives you more visibility of your data. Can significantly aid auditors in discovering knowledge hidden in data, confirming hypotheses and making the most of the available data. Reduce the scope of work. Improve the selection of samples for testing. It also would help with efficiency as we can use scripts for routine or periodic audits rather than manually performing an analysis.

As depicted in figure 4, automation-AI, data analytics, and tools such as Agile are clearly the most cited techniques considered best for minimizing resource usage on IS audit projects. Responses in figure 3 affirm the findings from Moffitt, Rozario, and Vasarhelyi (2018) which claimed robotic process automation (RPA) can automate rules-based repetitive and manual tasks. RPA is defined as a family of tools used to emulate user interface interactions in computer systems (Aguirre & Rodriguez, 2017). From the survey, 37% of respondents recommended data analytics as a way to accomplish more tasks with fewer resources. A related study by No, Lee, Huang, and Li (2019) asserted that data analytics helps in identifying anomalies allowing auditors to focus on items associated with higher risk. Participant 21 (P21) commented, “Use of data analytics to analyze data and identify exceptions (if any)". Participant 23 (P23) recommended a combination of automation and data analytics to improve the audit process, saying "To automate repetitive work and rely on humans in areas that require judgment. Also, use data analytics to determine areas that need to be focused on more (anomalies) so that more resources are allocated to work on that". This combination of automation and analytics enhances the agility of the IS audit process.

Figure 4. Accomplish More Tasks with Fewer Resources

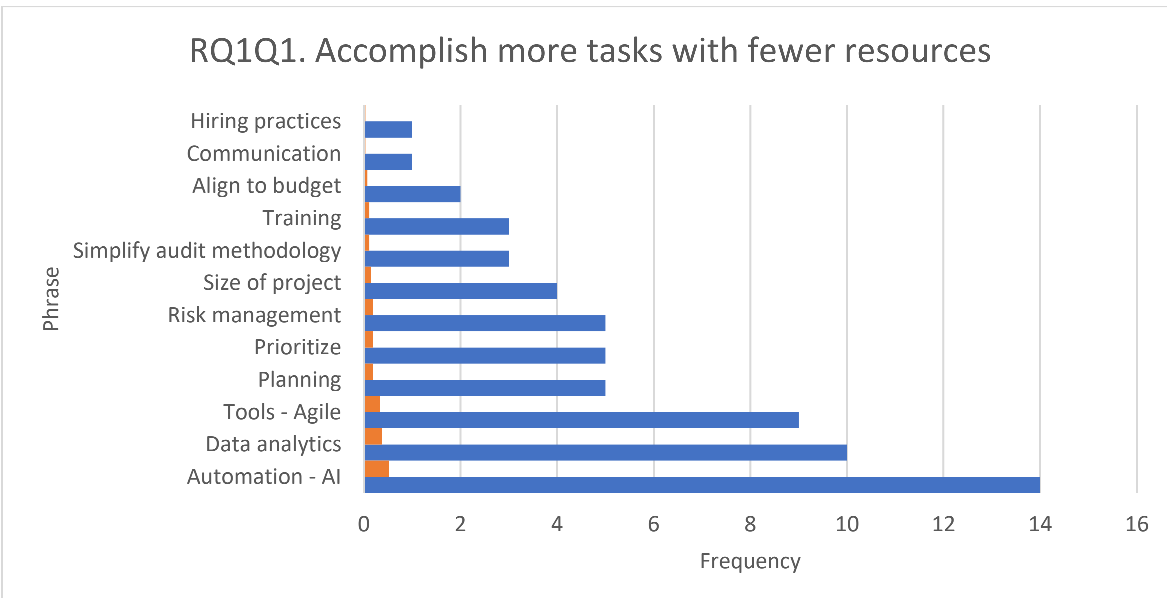


Figure 5. Concept Extraction - Accomplish More Tasks with Fewer Resources

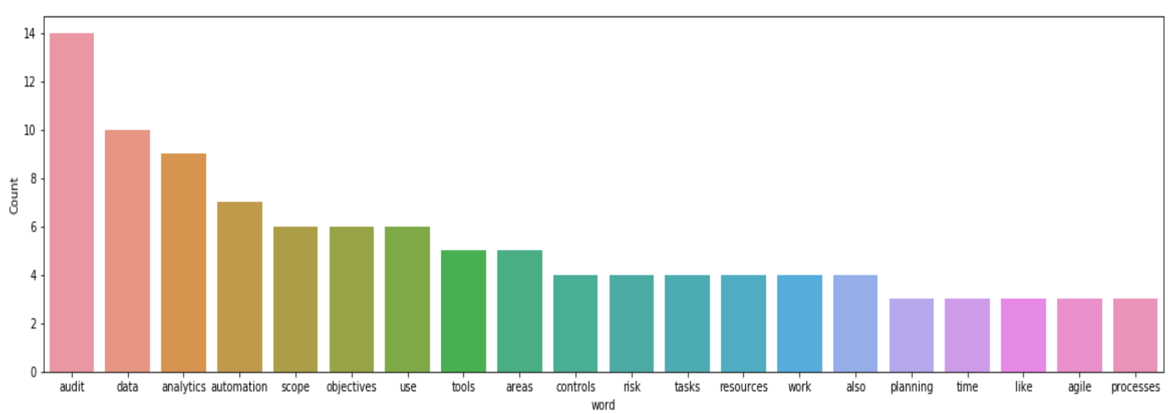
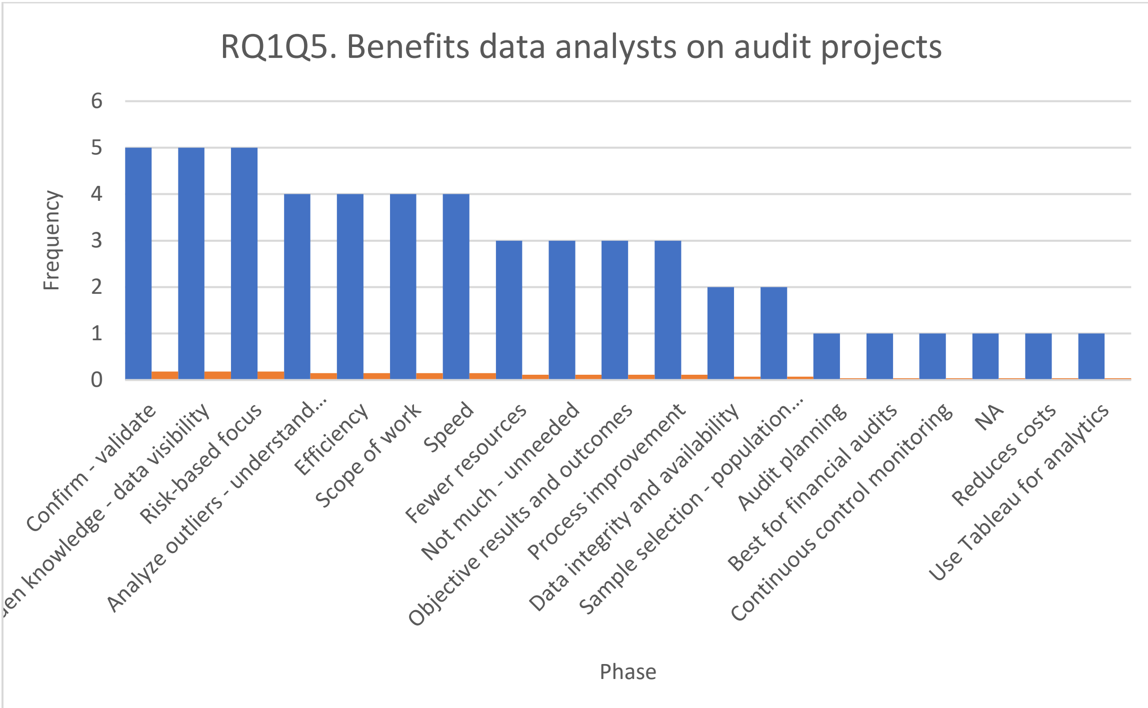


Figure 5 shows the results of the initial attempt at concept extraction based on the Apache OpenNLP chunker. A triangulation of the results of concept extraction against the NVIVO coding shows roughly about the same set of terms generated. Figure 5 results are only used as a validation set for credibility and consistency to RQ1. Question five of RQ1 explored IS audit practitioners' perceptions on the benefits of using data analytics on IS audits. As shown in figure 6 below, the most commonly cited benefits identified by respondents were evidence validation and confirmations, data visibility, and risk analysis.

Some respondents mentioned process efficiency, speed, and reduced scope of work as some of the significant benefits of using data analytics. There were many benefits identified in respondents' comments and most of them revolved around minimizing costs of IS audit projects. Some of the comments from respondents included: "Data analysis can significantly aid auditors in discovering knowledge hidden in data, confirming hypotheses and making the most of the available data" (P6); "Data Analytics gives you more visibility of your data and you are able to gain insights into your data which can help you make better decisions. In firms, DA can help automate processes/tasks thereby enabling teams to save on time and resources" (P7); "Quickly looking for exceptions and or comparison versus a set baseline or standard" (P16). All the benefits identified help reduce audit process labor costs. In a related study Gu, Simunic, and Stein (2017) found evidence of labor cost reduction with a shift in the nature of historical fixed cost thereby eliminating risks.

The researcher used the feedback from the four survey questions in table 8 to address RQ2. The four survey questions sought to establish if using data analytics in IS audit could help lower labor cost. RQ2 is the basis of the entire research; the frequency response from survey question 1 below indicated that 37% of respondents spend 10% of their audit projects budget on specialist services. Another 22% of respondents said they spend between 15% and 35% on hiring specialists to help with data analysis for their audit projects.

Figure 6. Benefits of Using Data Analytics on IS audits



RQ2: Can the cost of labor be lowered in information systems (IS) audit by utilizing data analytics?

In addition to this high reliance on specialists, 4% of the respondents claimed they spend their entire audit budget on specialists. Many responses to RQ2 survey questions were concerned with the lack of data analytics knowledge in the audit practice, most concerns were about increase in audit project costs.

Table 12

Frequency Table - Questionnaire for RQ2

Descending order of frequency responses based on No. of documents	No. of Docs (27)	% of 27 Docs
Survey Questions		
RQ2. Lower cost of labor	27	100%
Survey Q1. Percentage audit costs hiring specialists	27	100%
10% or fewer	10	37%
15% - 35%	6	22%
0%	4	15%
N/A	4	15%
Unsure	2	7%
Entire budget	1	4%
Survey Q2. Minimize number of specialists hired	27	100%
Training - Professional development	14	52%
Process automation - data analytics	9	33%
Systems access - integrated programs	5	19%
Hiring policies	2	7%
N/A	1	4%
Retain experienced employees	1	4%
Secondary school curriculum	1	4%

Table 13

Frequency Table - Questionnaire for RQ2 Continued

Descending order of frequency responses based on No. of documents	No. of Docs (27)	% of 27 Docs
Survey Q3. Specialists affect project cost	27	100%
Increases cost	22	81%
Cost containment	2	7%
N/A	2	7%
Other	1	4%
Survey Q4. In-house predictive analytics improves	27	100%
Identify problems & risks	13	48%
Insight – knowledge	12	44%
Planning – focus	11	41%
Confirm – validate	3	11%
Efficiency – effectiveness	3	11%
Speed	3	11%
Lean and efficient organization	2	7%
Reduces costs	2	7%
Reduces work and man hours	2	7%
Significantly improve	2	7%
Unsure	2	7%
Record time and skills	1	4%
Special projects	1	4%

Open coding enabled the researcher to capture IS audit practitioners' perceptions on the benefits of engaging data analysts and scientists as well as the proportions of analytical tasks on audit projects. Table 9 shows the open coding for RQ2. Some of the key benefits mentioned in participants' comments included: Hidden knowledge/data visibility – " Data analysis can significantly aid auditors in discovering knowledge hidden in data, confirming hypotheses and making the most of the available data" (P6); Cost Reduction/Speed Analysis – "A large scope of assurance using less resources" (P4), "Speed of solutions, data integrity and availability improved" (P5), "Reduce the scope of work and improve in the selection of samples for testing. It also would help with efficiency as we can use scripts for routine or periodic audits rather than manually performing an analysis. Also, scripts can be used for continuous control monitoring" (P17), "Significant cost savings due to reduction of time and resources required to complete an audit" (P20).

The researcher's inquiry on how engaging specialists affects project cost yielded mostly responses such as increases cost – "It would increase the project cost" (P16), "They drive cost up" (P18), "Increases expenses" (P15), "Increased cost" (P14), "In most cases the engagement of a specialist increases the cost of the project" (P13). There were a few respondents who felt engaging specialists on their project helped with containing IS audit project costs. On having in-house predictive analytics expertise, most respondents mentioned increased insights in the audit evidence and easier identification of problems and risks.

Table 14

Open Codes for RQ2

Open Code	Properties	Examples of Participants' Words
10% or fewer 15% - 35%	About 37% of respondents said 10% or less of the budget is expended on specialists. Another 22% of respondents felt 15% - 35% of budgets are spent on specialists.	5-10% Around 10% less than 10% Zero utilize internal resources.
Training – Professional development, Process automation – data analytics, Systems access – integrated programs	Most felt professional development targeting data analytics skills	Training. Continuous training of permanent audit staff. Process Automation. Training or professional development in the field. Using data analytic tools Staff development program Train staff on DA and tools, provide access to systems of record to audit staff so that they can self-service evidence.

Table 15

Open Codes for RQ2 Continued

Open Code	**Properties**	**Examples of Participants' Words**
Increases cost	Most agreed hiring specialists increases costs	Cost goes up but you get quality deliverables. It increases the project costs. It increases credibility and confidence. In most case it helps in shortening the time spend trying to research and figuring out issues. External resources generally cost more than internal efforts. Specialists often come at a premium in terms of fees or rates that they charge depending on the particular area of specialty, this can often result in increased costs if not suitably managed. Increased cost. Increased expenses. Adds about 20% to costs.

		It will increase however it's largely a function of cost benefit analysis.

Table 16

Open Codes for RQ2 Continued

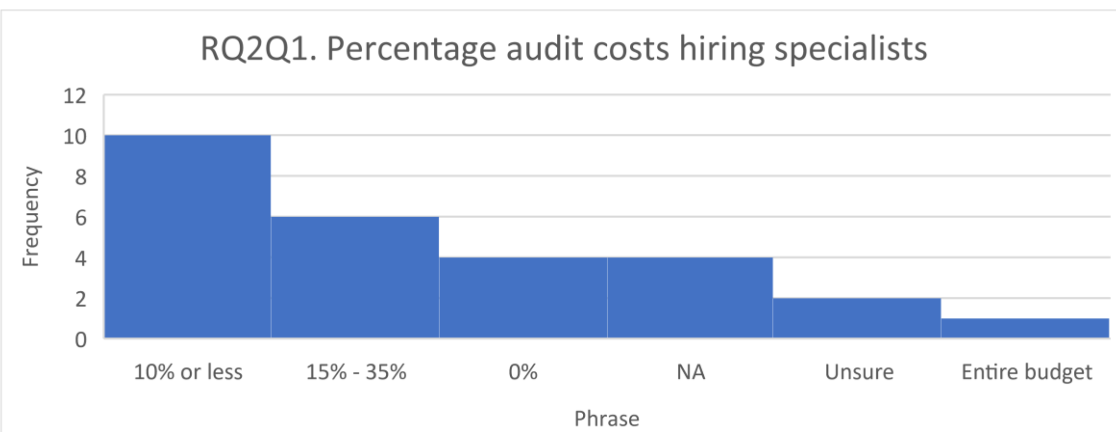
Open Code	**Properties**	**Examples of Participants' Words**
Identify problems & Skills, Insight- Knowledge, Planning - focus	Improve efficiency and effectiveness Helps reduce costs through insights Quick anomaly detection (Save time)	Gain deep insight fast. Results in focus on areas of high risks based on predictive analytics thereby saving project time and overall costs. It reduces licensing fees and cost of maintenance by vendors. By identifying outliers so that efforts can be concentrated, In-house predictive analytics could assist in directing audit teams towards areas where greater or urgent coverage is required. It takes away much of the work and man hours. It Increased efficiency and effectiveness.

		Save time, identify problem areas, Could help management identify problems before they occur Identify areas of high risk.

According to figure 7, more than 59% of respondents said they allocated 35% of their IS audit project costs to hiring specialists. There was a group of 15% of practitioners who claimed they do not hire any specialists on their projects while another 15% claimed specialists are not applicable to their projects. Two of the 27 respondents were not sure what percentage of their project costs is attributable to specialists on any of their projects.

Figure 8 summarizes the perceptions of IS audit practitioners on what can be done in the IS audit process to minimize the number of specialists' engagements. Some of the more popular recommendations included training, professional development, process automation with data analytics to enable practitioners to carry self-service analysis.

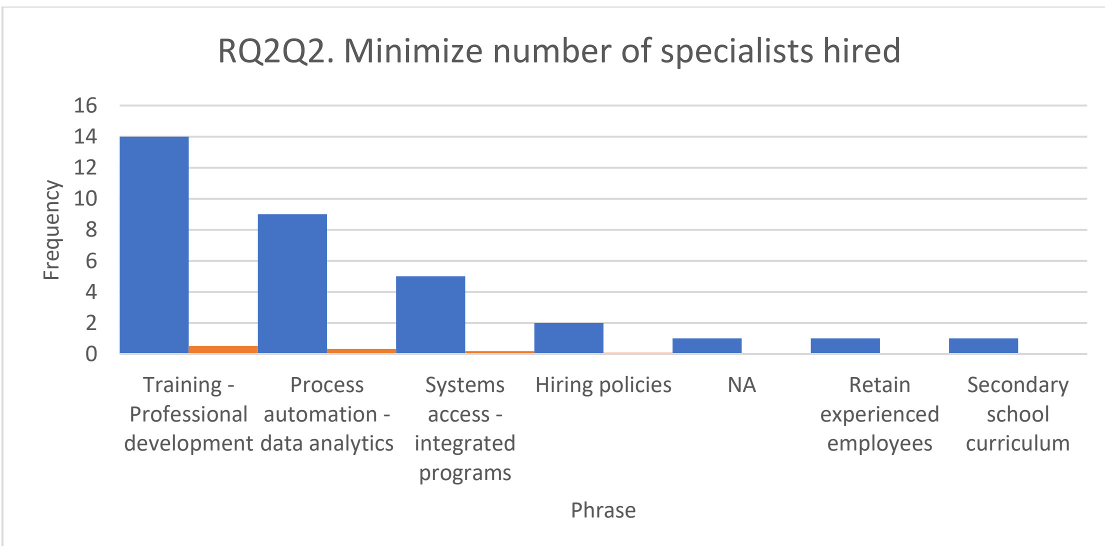
Figure 7. Percentage of Audit Costs of Hiring Specialists



Of the 27 respondents from the curated survey data, 52% recommended training audit practitioners on data analytics and 33% said audit process automation using data analytics techniques was a better cost containment approach.

Some of the comments from respondents included, “Train your own staff” (P1); “More training in special areas. Cross-training of auditors” (P6); and “Use more data analytics” (P14). There was another 19% of respondents who recommended moving to self-service data analytics by giving practitioners system access and training.

Figure 8. Minimize the Number of Specialists on IS Audits

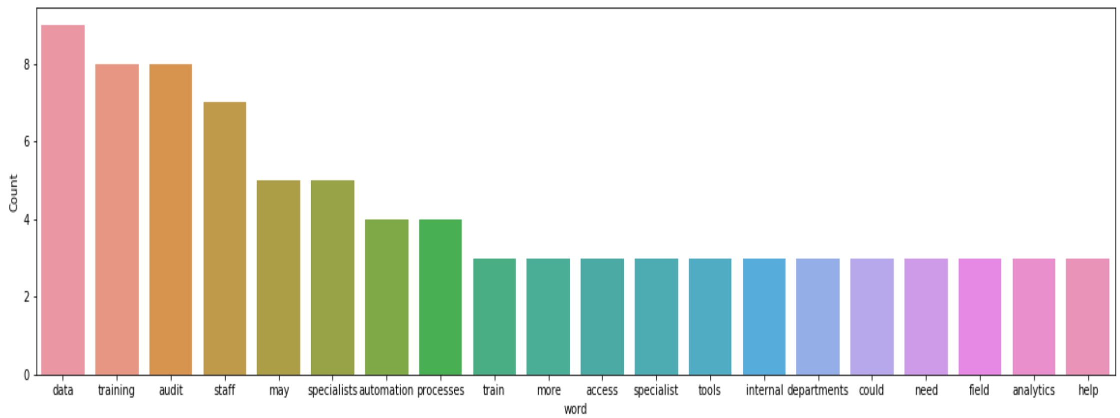


Some of the comments from respondents included, “Train your own staff” (P1); “More training in special areas. Cross-training of auditors” (P6); and “Use more data analytics” (P14). There was another 19% of respondents who recommended moving to self-service data analytics by giving practitioners system access and training.

Figure 9 shows the results of the initial attempt at concept extraction based on the Apache OpenNLP chunker. A triangulation of the results of concept extraction against the NVIVO coding shows roughly about the same set of terms generated. Figure 9 results are only used as a validation set for credibility and consistency to RQ2.

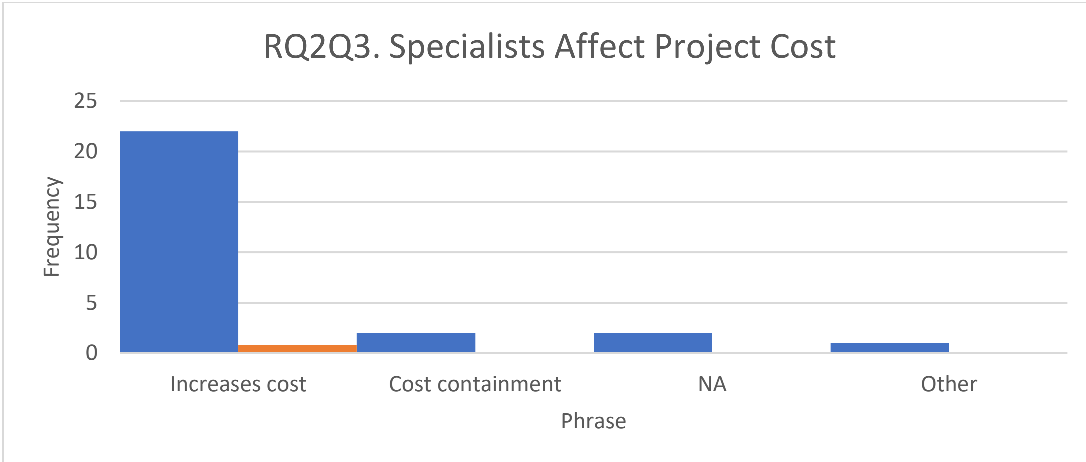
RQ2 survey question 3 responses, depicted in figure 10, showed 22 of the 27 respondents agreed that hiring specialists on an IS audit project was a major cause of cost increase that needed to be resolved. 81% of respondents agreed that specialists engagements were weighing heavily on IS audit project costs. Only 7% of respondents used specialists' engagement as a cost-containment strategy on their projects.

Figure 9. Concept Extraction - Minimize the Number of Specialists on IS Audits



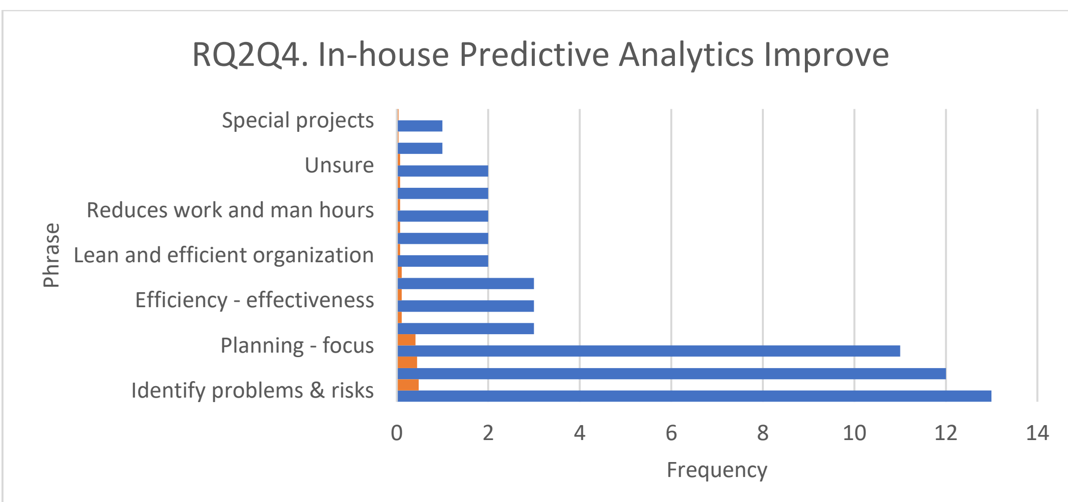
Some of the participants' comments regarding cost increases in engaging specialists were: "It actually increases the project costs" (P3); "Specialists often come at a premium in terms of fees or rates that they charge depending on the particular area of specialty, this can often result in increased costs if not suitably managed" (P11); and "Adds about 20% to costs" (P19). Survey question 4 of this section probed participants on the benefits of establishing in-house predictive analytics expertise within the IS audit practice. Figure 11 below shows there were 13 thematic benefits identified by respondents. The most popular benefits were the ability to identify problems and risks, and improvement in audit insights and knowledge.

Figure 10. Specialist Engagement Effect on Project Cost



These two benefits appeared in 25 of the 27 responses with 41% of respondents commenting that having in-house predictive analytics would enable IS auditors to focus on audit planning and their core competency areas. Some practitioners said in-house predictive analytics would significantly improve IS audit efficiency and effectiveness, reduce costs, reduce work, and person-hours.

Figure 11. Establish of In-house Predictive Analytics



RQ3: How could the use of a data analytics framework improve IS auditing?

The researcher used the data collected from the online survey to address RQ3. The researcher analyzed the frequency of responses for 27 IS audit practitioner participants to identify themes on how the use of a data analytics framework could improve IS auditing. Table 10 below shows an analysis of the four questions that were used to address RQ3. The majority of respondents indicated that a data analytics framework should be a separate framework designed as an extension to ITAF. Lack of knowledge about the ITAF, SAS No.56, and SAS No.94 within the IS audit practice revealed the gap in standard procedures and guiding framework enforcement in the practice. The researcher provided the links to text of SAS No.56 and 94 to refresh practitioners on specific requirements for internal control.

Table 10

Frequency Table - Questionnaire for RQ3

Descending order of frequency responses based on No. of documents	**No. of Docs (27)**	**% of 27 Docs**
Survey Questions		
RQ3. Use of Data Analytics framework	27	100%
Survey Q1. Changes to ITAF use DA	27	100%
Unsure	7	26%
Raise awareness - provide guidance	6	22%
Sufficient now	6	22%
Changes to framework	5	19%
General purpose of using DA	5	19%
Survey Q2. DA framework improve audit	27	100%

Table 10

Frequency Table - Questionnaire for RQ3 Continued

Descending order of frequency responses based on No. of documents	No. of Docs (27)	% of 27 Docs
Manage risk - compliance – security	9	33%
Planning – focus	8	30%
Cost reduction	5	19%
Accuracy – completeness	3	11%
Sample selection - population mining	3	11%
Unsure	3	11%
More efficient	2	7%
Time	2	7%
General benefit to company	1	4%
Sufficient now	1	4%
Survey Q3. DA framework SAS No. 94	27	100%
Unsure	9	33%
Efficacy	7	26%
Consistency	3	11%
Monitoring	3	11%
Reduce risks	3	11%
Accuracy	2	7%
Complex calculations	2	7%
Documentation	2	7%

Table 10

Frequency Table - Questionnaire for RQ3 Continued

Descending order of frequency responses based on No. of documents	No. of Docs (27)	% of 27 Docs
Legislation - code of conduct	2	7%
Objective results	2	7%
Processing large volumes of data	2	7%
Additional analysis	1	4%
Availability of information	1	4%
Data-focused approach	1	4%
Insights	1	4%
IS Audit Universe	1	4%
Issues relying on DA	1	4%
Reduce audit procedures	1	4%
Timeliness of information	1	4%
Survey Q4. DA compliance SAS No. 56	27	100%
Unsure	9	33%
Efficacy	7	26%
Insights	4	15%
Planning	4	15%
Accuracy	2	7%
Increases need to comply	2	7%

Table 10

Frequency Table - Questionnaire for RQ3 Continued

Descending order of frequency responses based on No. of documents	**No. of Docs (27)**	**% of 27 Docs**
Reduce audit procedures	2	7%
Audit evidence	1	4%
Consistency	1	4%
Detect fraud	1	4%
Objective results	1	4%
Overrides	1	4%

On the importance of a data analytics framework in the IS audit process, open coding revealed that most practitioners are "unsure" of ITAF, SAS No.56, and SAS No.94 requirements. Regarding the value of data analytics to improve planning and review of audits, most respondents mentioned "makes it easy to manage risk," "compliance," "security", and "audit planning." Some of the comments included, "Improve data accessibility with security protocols" (P5); "For audit planning, data can help the audit team zero in on where to spend time interviewing" (P10); "A well formulated framework would assist in directing the efforts of audit teams, i.e. those that are tasked with analytics so that they can make the best use of data analytics" (P11); "Cost reduction" (P14); and "More efficient" (P27). Table 11 shows the open codes for research question three.

Table 17

Open Codes for RQ3

Open Code	**Properties**	**Examples of Participants' Words**
Unsure, Raise awareness – provide guidance, Sufficient now.	Most had no knowledge of ITAF. Some felt ITAF is sufficient.	"Raise the awareness of information assurance and automate the process"; "In my understanding, the ITAF framework speaks well of the use of tools and techniques in the Audit process and encourages use of CAATs"; "It is quite sufficient for the framework to encourage such"; "My opinion is that the framework cannot be justified to go on to encouraging specific tools to use so what it says now is sufficient"; "I think it's sufficient for now"; "I have little exposure to the framework but generally I feel that any framework should be an enabler of a process, so given the demonstrated benefits of data analytics, I would suggest that measures be taken to align the benefits to the provision of the framework so that data analytics can be leveraged even more".

Manage risk – Compliance – security, Planning focus, Cost reduction	Most mentioned cost reduction and efficiency of the process	"Helps you focus on outliers which maybe areas of risk"; "It would give more conclusive results"; "Eliminates material misstatements"; "For audit planning, data can help the audit team zero in on where to spend time interviewing"; "Improve the testing of complete sets of data rather than samples"; "Aiding risk assessment through identification of anomalies and trends, perhaps even through comparison to industry data, pointing auditors toward items they need to investigate further"; "Technology permits more frequent or continuous monitoring of transactions by external auditors"; "It would improve identify areas of fraud; it would improve the scoping and sample selection for the audit; it would help with improving audit coverage

		reduce man hours and budget constraints”; “Could allow more information to be extracted from population data, and possibly contribute to lower audit costs”; “This will reduce the execution time frame hence lower the overall cost”; “More efficient”.
Unsure, Efficacy, Consistency, Monitoring, Reduce risks	Most had no knowledge of SAS No.94, Improve process efficiency and reduce cost	“Helps reduce numbers of substantive audit procedures. Not sure”; “Create more objective results from evidence of transactions by offering a comprehensive coverage of IS Audit Universe”; “not an expert in SAS”; “Unsure”; “Improve efficiency and effectiveness”; “It facilitates achievement of 6 objectives on efficiency and effectiveness of audits”;

		"This will make the requirement more robust"; "Don't know".
Unsure, Efficacy, Insights, Planning	Most had no knowledge of SAS No.56, Some cited provision of efficacy and insights, Some said improve planning	"Create more objective results from evidence of transactions"; "Not sure"; "There will be increased need to comply with SAS No.56"; "Data analytics used to happen during the field stage of the audit but SAS 56 it can now happen in the planning stages"; "Analytical procedures are an important part of the audit process and consist of evaluations of financial information made by a study of plausible relationships among both financial and nonfinancial data"; "Analytical procedures range from simple comparisons to the use of complex models involving many relationships and elements of data"; "A basic premise underlying the application of analytical procedures is that plausible relationships among data may reasonably be expected

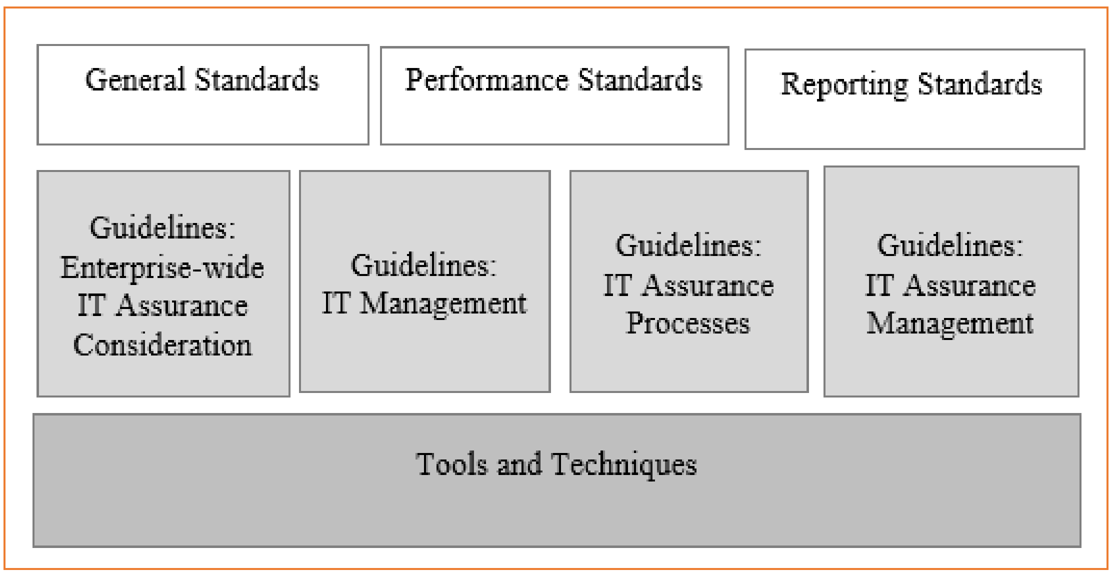
		to exist and continue in the absence of known conditions to the contrary"; "Particular conditions that can cause variations in these relationships include, for example, specific unusual transactions or events, accounting changes, business changes, random fluctuations, or misstatements"; "Use of data analytics in the IS audit process may positively affect compliance with SAS No 56 in that efficiency will be achieved"; "Time and resources on most of the planning and review processes may be cut by significant margins"; "Making compliance more efficient with less effort is always appreciated"; "There are aspects of the IS audit process such as planning and execution where the focused analysis of data could provide valuable input into planning and also providing irrefutable evidence which impacts the quality of audit conclusions

		reached, so I feel that there is a lot to be leveraged from that regard”; “Unsure”; “With data analytics, analytical procedures will become easier for IS audit”; “More expedient to comply with SAS No 56”.

The frequency responses regarding open coding indicated 7 of the 27 respondents indicated they were unsure of possible changes that could be made to ITAF to pave the way for analytics. Data suggested a substantial percentage of IS audit practitioners are unaware of the use of ITAF and its requirements as a guiding framework. According to ISACA (2019), ITAF provides a single framework through which IS audit and assurance professionals can acquire knowledge on how to use audit tools and techniques. Figure 12 below shows components of ITAF, displaying a section dedicated to address tools and techniques in its implementation. The top part of the framework addresses reporting guidelines for evidence and other relevant standards ensuring completeness of IS audits. The middle part of the framework in figure 12 shows four different sets of guidelines that provide direction for adoption of the four standards sets shown in the top part of the framework.

The frequency response from survey question 2 shown in Figure 13 below indicates a data analytics framework could improve planning and review of audits through improved compliance, risk management, and security. About 60% of respondents felt the use of a analytics framework could provide guidance and standardize how auditors can leverage analytics. One respondent commented, “A well formulated framework would assist in directing the efforts of audit teams, i.e. those that are tasked with analytics so that they can make the best use of data analytics.” (P11). Other respondents cited standardized sample size selection, completeness of evidence, cost reduction, efficiency improvements, as well as reliability of findings.

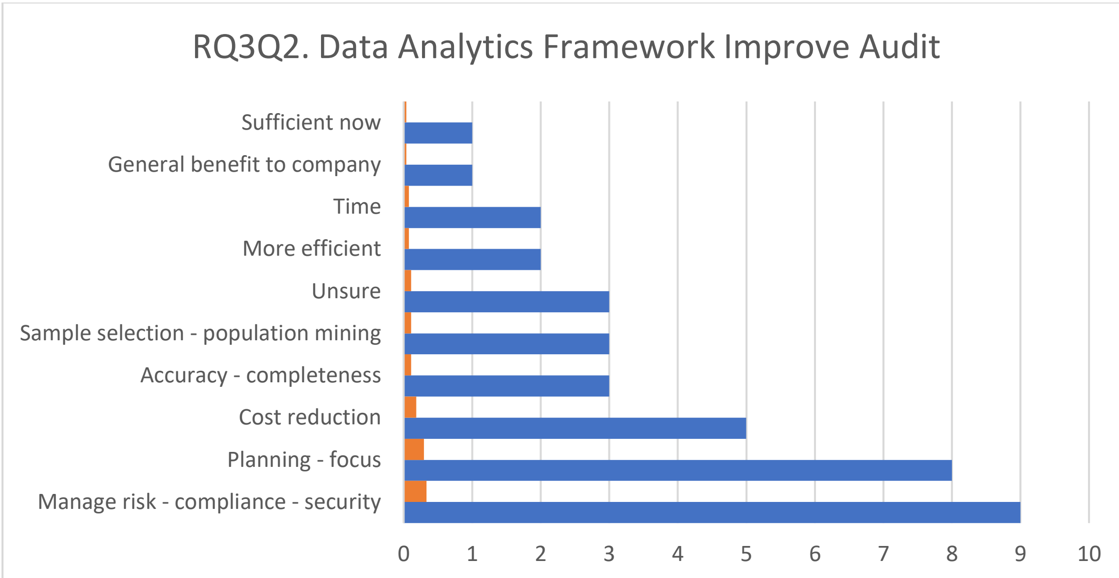
Figure 12. ITAF 3rd Edition – How ITAF is Organized Hierarchically



Cited from ISACA (2019) IS audit and Assurance Guidance Resources.http://www.isaca.org/Knowledge-Center/Research/Documents/ITAF-3rd-Edition_fmk_Eng_1014.pdf?regnum=530348

One participant’s comment said use of data analytics “Could allow more information to be extracted from population data, and possibly contribute to lower audit costs” (P19).

Figure 13. Data Analytics Framework on Planning



According to Tucker (2001), SAS No.94 provides guidance on the impact of technology on independent audits. This standard was originally proposed for internal control on financial audits. The frequency response from survey question 3 shown in table 9 on Page 103 above revealed that SAS No.94 may still be relevant in guiding IS and financial audits. Most responses regarding adopting a data analytics framework for IS auditing concur with Omoteso (2016) that it would enhance SAS No.94's validity by improving IS audit accuracy, reducing risk, providing consistency, and simplifying audit evidence document generation. An analysis of the open codes for RQ3Q4 responses showed that 62% of respondents felt the use of data analytics in IS audit improves compliance with SAS No.56 through reduced tasks and compelling insights produced. About 33% of respondents were unsure how the use of data analytics could affect SAS No.56; this is consistent with responses on SAS No.94 and ITAF requirements.

Selective Coding

Selective coding, the third phase, involved the extraction of a core variable based on all data collected. Selective coding helped document categories related to minimizing IS audit labor cost, the core theme of the study. After the researcher identified the core variable, data not related to the core variable was removed from the analysis. Table 12 below shows the three comparisons of open, axial, and selective coding.

Table 18

Axial codes and Selective code based on the Open codes

Open Code	**Axial Codes**	**Selective Code**
Comparisons – Testing, Sample Selection, Team size, Percentage of man-hours on DA (50%), Percentage of Specialist labor (59%).	Specialist Labor Cost	Wanting to minimize IS audit labor cost
Increases cost, 15-35% cost, Confirm -	Complex Manual Tasks	

validate, Hidden-knowledge – data Visibility, Risk-based focus, Analyze outliers, Understand Themes, Efficiency, Fewer resources, Speed, Scope of work.		
Automation – AI, Data Analytics, Process	Digital Labor	

automation - data analytics, Effectiveness, Efficiency, Significantly Improve.		
Changes to framework, General purpose of using DA, Agile Tools, Manage Risk, Compliance, Security, Cost Reduction, Accuracy –	Guiding Framework	

Completeness, Standardize sampling, Systems access – Integrated programs.		
Hiring practices, Efficiency – Effectiveness, Speed, Reduce costs, Reduce work and man hours.	In-house Analytics Expertise	
Training – Professional development, School curriculum	Data Analytics Training	

change, Training.		
Governance and security, Risk Management, Identify problems and risks, Manage risk - compliance - security	Reduce Risk and Labor Cost	

Theoretical Coding

Theoretical coding involves integration and refinement of categories to establish conceptual relations between substantive codes (Urquhart & Fernández, 2016). Theoretical coding exposes emerging relationships derived from axial coding (Charmaz, 2014). It also helps the researcher to develop, explain, and write the storyline of the interaction of the themes (Thornberg & Charmaz, 2014). As the researcher worked through axial and theoretical coding, seven themes emerged:

1. Specialist labor cost: The core category around which all other categories revolved (the what).

2. Complex manual tasks: Complex and manual repetitive work drive external resource engagements (the why).
3. Digital labor: Promote efficiency and effective use of resources to reduce cost of leveraging data analytics (the how).
4. Data Analytics Training: Professional development to improving data analytics expertise for IS auditors (the how).
5. Guiding framework: Standardizes processes, enhances efficiency and effective use of resources (the how).
6. In-house Analytics Expertise: Promotes self-service analytics and automation (the how).
7. Reduce Risk and Labor Cost: Sustaining objective of auditing (consequences).

Saturation

Saturation happens when gathering new data yields, no new theoretical insights related to the properties of the core categories (Charmaz, 2014). The analysis of participants' responses continued through the first 27 respondents, which was two participants above the sample proposed in the initial plan. Table 13 below is a summary of the themes that emerged from the first eleven participants' responses. These responses were downloaded and coded before the third reminder was sent on October 10, 2019, as shown in Table 5 on page 78. Six themes emerged in establishing the significance of data analytics in reducing labor costs in the IS audit process.

Table 19

Themes that affect IS Audit Labor Cost

Themes	***Participants***	***Percentage***	***Participants by Numbers***

Digital Labor	11	100%	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
Specialist labor cost	11	100%	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
In-house Analytics expertise	11	100%	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
Data Analytics Training	10	91%	1, 2, 3, 4, 5, 6, 7, 9, 10, 11
Reduce Risk and Labor Cost	9	82%	1, 2, 3, 4, 6, 7, 9, 10, 11
DA Framework	7	64%	1, 2, 5, 6, 9, 10, 11

Note: Population size is 11 participants.

Table 14 is a summary of the emergent themes from the 27 participants responses. The six themes listed in Table 13 were viewed as the most significant factors needed to help minimize labor costs and improve efficiency in the IS audit process by the 27 participants. The percentage frequency of the themes shifted a little for specialist labor cost impact, but the order seemed consistent with the results from table 13. The same six themes continued to surface even though the order had changed; therefore, data saturation had occurred.

Table 20

Factors that affect IS Audit Labor Cost

Themes	***Participants***	***Percentage***	***Participants by Numbers***
Digital Labor	25	93%	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 27

In-house Analytics Expertise	25	93%	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 21, 22, 23, 24, 25, 26, 27
Specialist Labor Cost	24	88%	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18,19, 21, 24, 25, 26, 27
Data Analytics Training	23	85%	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18,19, 20, 21, 24, 26, 27
Complex Manual Tasks	23	85%	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 16, 17, 18,19, 20, 21, 23, 26, 27
Reduce Risk and Labor Cost	20	74%	1, 2, 3, 4, 6, 7, 9, 10, 11, 12, 13, 15, 16, 17, 19, 20, 21, 24, 26, 27
DA Framework	18	67%	1, 2, 5, 6, 9, 10, 11, 13, 14, 16, 17, 18, 19, 20, 21, 24, 26, 27

Note: Population size is 27 participants.

Theoretical Sampling

Theoretical sampling enabled the researcher to continue collecting survey responses until there were no new concepts and themes emerging from additional data (Butler, Copnell, & Hall, 2018; Thornberg, 2017). After deriving the open and axial codes from the first 11 respondents, theoretical sampling was no longer considered necessary. The seven categories that emerged on the initial analysis captured most of the perceptions of the survey participants.

Memo Writing

Memo writing was conducted throughout the entire data collection and constant comparative analysis processes. Memos are conceptual notes taken by the researcher during coding to theorize the codes based on their interrelationships (Lapan, Quartaroli, & Riemer, 2012, p.54). While conducting the initial coding, the researcher utilized memos which helped capture perceptions of the participants regarding the impact of data analytics in reducing labor costs in the IS audit process.

Results

Results of the survey data collection and the constant comparative analysis of the 27 participants responses addressed the main research question. These results specifically targeted the following three research questions.

RQ1: How can the application of data analytics in information systems (IS) audit improve the IS audit process?

RQ2: Can the cost of labor be lowered in information systems (IS) audit by utilizing data analytics?

RQ3: How could the use of data analytics framework improve IS auditing?

Grounded in how data analytics could help lower IS audit labor costs (as shown in Table 14), the IS Audit Digital Labor Cost Theory in Figure 11 helps to reveal factors determining the level of labor cost in audits. Basically, it proves that eliminating complex manual tasks in the audit process through data analytics-driven automation reduces labor costs. Most respondents cited artificial intelligence and RPA as the two data analytics approaches that could help minimize labor costs. The researcher categorized automation through all identified techniques as digital labor. Some respondents also cited providing data analytics training to internal staff and hiring IS auditors with data analytics expertise as other way to minimize labor costs incurred in hiring specialists. There were seven participants who said that in addition to adopting data analytics in the IS audit process, defining a data analytics framework for the IS audit process or extending the existing ITAF framework could also help improve efficiency and effectiveness of the audit process.

Specialist Labor Cost

Labor cost lies at the heart of this research and forms the root of the "what" theme as outlined on page 118. High IS audit cost is coded into labor cost and the term resonates with practitioners in the field. Labor cost includes core IS audit team labor cost to specialists' engagement cost. Some of the responses regarding impact of engaging specialists on IS audit projects affect project cost included: "In most cases, the engagement of a specialist increases the cost of the project" (P13) and "It can be a significant cost to hire outside help. To make matters worse, if the outside help is not well integrated into the effort it can severely affect the quality of the result. This ultimately decreases the return on investment, potentially to zero." (P24). Some of the respondents claimed engaging specialists brings cost awareness as teams leverage the specialists in ways that shorten research time. Participant number six claimed, "In most cases, it helps in shortening the time spent trying to research and figuring out issues" and participant number seven commented that "Engaging specialists results in specialists being aware of the need to complete projects within budgeted time and costs thereby containment of overall costs”. The major of activities of the IS audit process identified as driving labor cost were associated with data analysis. Responding to the question, what percentage of your work time do you spend on data analysis, 74% of participants claimed they spend between 20 and 50% of their project work time on data analysis.

Another factor strongly emphasized in responses from participants was that of establishing in-house predictive analytics. One respondent said, “Focus on areas of high risks based on predictive analytics thereby saving project time and overall costs.” (P7). Other respondents said: “It reduces licensing fees and cost of maintenance by vendors” (P9); “It takes away much of the work and man-hours” (P18); and “Could help management identify problems before they occur” (P27).

Complex Manual Tasks

The complex manual tasks category reveals the most frequently cited underlying reason why IS audit project costs continue to rise. This category refers to why IS audit costs continue to be high, although technology and innovation have accelerated savings in other business areas. Most respondents felt hiring specialists; the ratio of specialists on projects; and manual repetitive tasks are the underlying drivers of labor cost. Some comments from respondents pointed to artificial intelligence, automation, and data analytics as better options to minimize rising IS audit costs. Participants 16 and 27 recommended bots and robotic process automation (RPA) as a way to minimize labor costs on IS audits. Bots can be used to automatically conduct audits while interacting with human responses (Raschke, Saiewitz, Kachroo, & Lennard, 2018). Bots are among data analytics techniques built by data scientists using deep learning’s neural network algorithms. Deep learning is one of the cutting-edge data analytics techniques

(Najafabadi, Villanustre, Khoshgoftaar, Seliya, Wald, & Muharemagic, 2015). According to Moffitt, Rozario, and Vasarhelyi, (2018) RPA is another innovative technology being used to automate manual repetitive tasks and, as such, could be leveraged in some of the IS audit tasks to curb labor costs.

Digital Labor

This category refers to how the use of technology, and specifically the adoption of data analytics in the IS audit process, can help minimize labor costs and improve efficiency. Responses regarding solutions in the IS audit practice to help teams accomplish more tasks with fewer resources all point to digital labor. According to Kokina and Blanchette (2019), digital labor is defined as the use of technology to replace human workers leveraging data analytics techniques and RPA. Comments from respondents on accomplishing more with fewer resources pointed to artificial intelligence, automation, and data analytics as better options to minimize rising IS audit costs. Some comments from participants included: “Building automation like AI” (P3); “Automation and training” (P4); “Automation - if more tasks could be automated, that will ensure that teams save time and resources and be able to complete more tasks” (P7); and “adoption of data analytics” (P14). Deep learning is one of the up-and-coming data analytics techniques (Najafabadi, Villanustre, Khoshgoftaar, Seliya, Wald, & Muharemagic, 2015). According to Moffitt, Rozario, and Vasarhelyi (2018), RPA is also another proliferating technology being used to automate manual repetitive tasks and, as such, could be leveraged in some of the IS audit tasks to curb labor costs.

Data Analytics Training

This category refers to how the enforcement of data analytics training and education could help minimize labor costs and improve efficiency in the IS audit process. In responding to what could be done in the IS audit practice to help teams accomplish more tasks with fewer resources, most participants recommended data analytics training. Some of the comments from participants included: "Automation and training" (P4); "Train the IT staff to think like auditors, so that the help that we ask for is easier to get" (P12); and "Hire smarter and more capable people" (P26). In another survey question posted to probe what can be implemented in the IS audit process to minimize the number of specialists hired, most respondents recommended training internal audit staff. Some common participants' responses included: "Train your own staff" (P1); "Access to courses that are relevant" (P2); "Training" (P3); "Continuous training of permanent audit staff" (P4); "More training in special areas. Cross training of auditors" (P6); "Training the IS Auditor" (P8); and "Training or professional development in the particular field. This may include formal courses or discussion with individuals possessing expertise in the relevant field for the purpose of enhancing the auditor's own capacity to deal with matters in that field" (P13).

Guiding Framework

This category established how having a data analytics framework in the current IS audit framework would help improve efficiency and effectiveness. Willis (1996) defined a framework as a conceptual structure intended to provide guidance for the use of tools and methods. A Guiding framework provides a structure on how the adoption of a data analytics for IS audit addresses the SAS No.94 requirements to provide adequate assessment of internal controls in information technology systems. Efficiency, in this case, refers to the ability to avoid expending a lot of resources and time when carrying out IS audit process tasks. Effectiveness in IS audit refers to the ability to achieve assurance services of the expected quality.

Respondents expressed concerns regarding the importance of efficiency in light of the need to accomplish more with fewer resources. In order to minimize labor cost in the IS audit process, most respondents pointed to automation with artificial intelligence, data analytics, and RPA. Some respondents recommended providing data analytics training to IS audit professionals so they can automate tasks and carry out self-service analysis.

Effectiveness is concerned with the need to pursue the target assurance goals on compliance, governance, and risk. One of the goals of auditing is the assurance of compliance with regulatory requirements, which would minimize labor costs if businesses do not have to repeat audits. Effective audit teams avoid repeat audits and deliver useful outputs.

This study was focused on whether the use of data analytics could help minimize labor costs on IS audits. The feedback from participants of the study pointed more to the efficient use of existing resources specifically in having IS teams with in-house data analytics capabilities to automate audits. Simply put, the fewer the number of outside specialists on IS audit projects, the better the labor costs are managed.

Most respondents were not acquainted with analytical procedures required as part of SAS No.56 and SAS No.94. A few respondents who acknowledged awareness of these analytical procedures agreed there are efficient and cost-effective benefits to having a data analytics framework. Participant number five commented: “improve data accessibility with security protocols”; participant 14 said, “cost reduction”; participant 15 said, “Prove consistency to planning and review of audits”; participant 18 mentioned, “reduce man-hours and budget constraints”.

In-house Analytics Expertise

This category also established how the use of data analytics in the IS audit process can help to minimize labor costs and improve efficiency. Most responses from participants on the impact of internal analytics expertise indicated there are potential cost reduction and efficiency improvements in maintaining in-house expertise. Most comments from respondents included the following phrases: “identify problems & risks”, “insight – knowledge”, “planning – focus”, “confirm – validate”, “efficiency – effectiveness”, “speed”, “reduces costs”, and “reduces work and man-hours”. Many respondents concurred that process automation requires internal expertise to maintain and improve performance on continuous monitoring. Some participants identified efficiency and effectiveness as significant benefits of having in-house predictive analytics expertise. There were responses such as, “Significantly improve the process where an audit is data intensive. On most audits the impact will be minimal as most audits are process based” (P25); “Save time, identify problem areas” (P22); and “Increased efficiency and effectiveness” (P21).

Reduce Risk and Labor Cost

The ultimate goal of IS audit work is to improve regulatory compliance, governance, and security. This category focused on the consequences of applying efficiency and effective audit techniques to these goals. Results suggest the adoption of a data analytics framework in the IS audit would help with standardization, efficient use of time, and other resources to reduce risk and labor costs. IS audit focuses on the assurance of regulatory compliance, security of systems, and governance of an IS environment. Labor cost is the main theme of this study, but it is incurred in an effort to provide assurance for reduced risk. Most participants commented that data analytics could help: "Identify areas of higher risk-presumably where outliers are identified" (P27); "Identify inherent and residual risk for each process which helps to prioritize the areas requiring the most attention" (P6); "Helps in planning audits which focus on area of high risk" (P1); "By providing assurance on risks that matters" (P4); "Cost reduction" (P14).

Themes Summary

Based on figure 4 analysis, 89% of participants reflected on the challenges of conducting IS audits at the lowest cost and they all recommended some form of automation through data analytics. Table 15 represents the themes and some key quotes supporting the derived themes. Some of these comments have already been discussed in the section above.

Table 21

Themes and Supporting Comments

Themes	***Participants Comments***
Specialist Labor Cost	"In most cases, the engagement of a specialist increases the cost of the project". (P13). "It can be a significant cost to hire outside help. To make matters worse, if the outside help is not well integrated into the effort it can severely impact the quality of the result. This ultimately decreases the return on investment, potentially to zero". (P24). "Cost goes up, but you get quality deliverables". (P1).

	"It actually increases the project costs". (P4).
Complex Manual Tasks	"Automation of repetitive tasks such as evidence collection and population testing". (P19). "25-30 %" (P9). "No more than 20% of my time at present, but I need to increase that to over 50% across many types of audits." (P11). "It's throughout every stage from planning to review, about 80% of our time we are focused on analytical work". (P20). "Agile Auditing". (P25).
Digital Labor	"Building automation like AI". (P3). "Automation and training". (P4). "Automation - If more tasks could be automated, that will ensure that teams save time and resources and be able to complete more tasks". (P7). "adoption of data analytics". (P14). "Automation using programs, scripts or bots to validate systems." (P16). "Automation. Increase the use of Robotics. Use newer and more nimble methodologies such as Agile Auditing". (P27).
Data Analytics Training	"Automation and training". (P4). "Train the IT staff to think like auditors, so that the help that we ask for is easier to get". (P12).

	"Hire smarter and more capable people". (P26). "Train your own staff". (P1). "Access to courses that are relevant". (P2). "Continuous training of permanent audit staff". (P4). "More training in special areas. Cross training of auditors". (P6). "Training or professional development in a particular field. This may include formal courses or discussion with individuals possessing expertise in the relevant field for the purpose of enhancing the auditor's own capacity to deal with matters in that field". (P13).
Guiding Framework	"It would give more conclusive results". (P2). "Improve data accessibility with security protocols". (P5). "A well-formulated framework would assist in directing the efforts of audit teams, i.e. those that are tasked with analytics so that they can make the best use of data analytics.". (P11). "Cost reduction". (P14). "Prove consistency to planning and review of audits". (P15). "Reduce man hours and budget constraints". (P18). "More efficient". (P27).

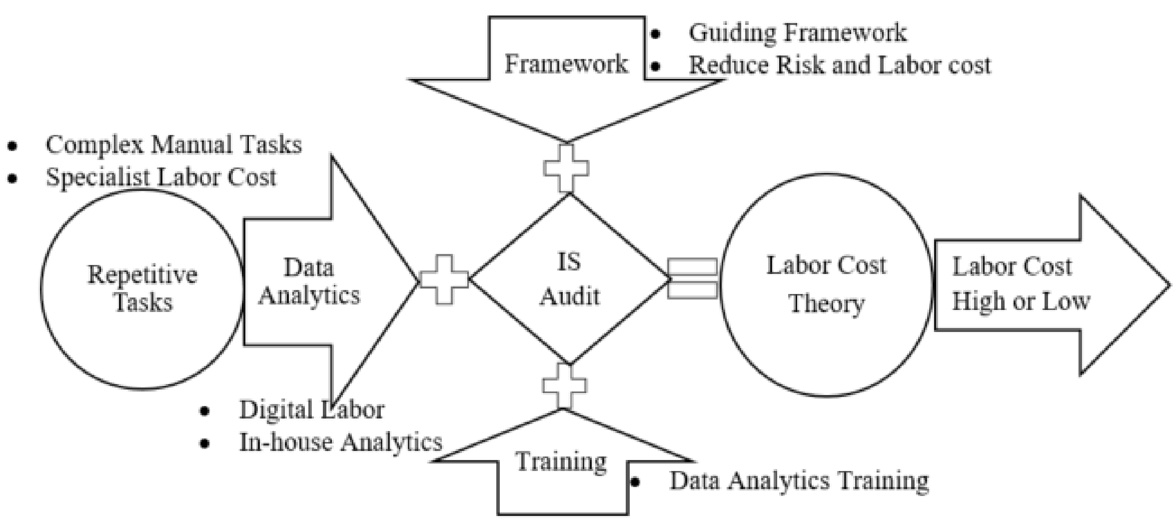
In-house Analytics Expertise	"Helps in planning audits which focus on area of high risk". (P1). "Significantly improve the process where an audit is data intensive. On most audits the impact will be minimal as most audits are process based". (P25). "Save time, identify problem areas". (P22). "Increased efficiency and effectiveness". (P21).
Reduce Risk and Labor Cost	"Identify areas of higher risk-presumably where outliers are identified". (P27). "Identify inherent and residual risk for each process which helps to prioritize the areas requiring the most attention". (P6). "Helps in planning audits which focus on area of high risk". (P1). "By providing assurance on risks that matters". (P4). "Cost reduction". (P14).

The general research question is: How could the use of data analytics in information systems auditing improve efficiency and minimize costs?

In figure 14 below the grounded theory of IS Digital Labor Cost established factors that affect the cost and the efficiency of the IS audit process. The use of data analytics leveraging a guiding framework to automate repetitive manual tasks results in lower labor cost and improved process efficiency provided audit teams have relevant training in analytics. The theory also revealed the importance of automation through data analytics techniques, which are listed as digital labor. In this study, digital labor denoted data analytics automation-based techniques like AI, RPA, machine learning, deep learning, and simulation. When digital labor is applied through a guiding framework by trained auditors labor cost is minimized, and efficiency of the IS audit process improves. Having in-house digital labor was also shown as a factor affecting labor cost. In addition to reduced labor cost, the organization will also reduce risk and improve assurance. From the data, it appears data analytics may chiefly change the IS audit process by eliminating human manual work through automation.

A related study by Kokina, Julia, and Davenport (2017) explored the implications of artificial intelligence (AI) automation on human auditors and the audit process. Their findings agree with this current study: there are certain specific tasks in IS audit which can be automated with the use of data analytics. Kokina, Julia, and Davenport (2017) listed machine learning, neural networks, natural language processing, deep learning, and robots as some of the major techniques that will revolutionize the auditing profession.

Figure 14. The Grounded Theory: IS Digital Labor Cost



Summary

The purpose of this qualitative study was to understand how the use of data analytics in the IS audit process can help minimize labor cost. A pilot study was conducted to validate the survey instrument. The pilot study surveyed three participants. The main study used data collected from 27 participants who were members of ISACA and experienced audit professionals having appropriate certifications.

This chapter involved the discussion of the research setting, the survey participant's qualifications, data collection, and analysis of participant feedback. The discussion of the initial, axial, selective, and theoretical coding along with the primary themes establish how the use of data analytics in the IS audit process can help minimize labor costs. Chapter 4 also discussed theoretical saturation and memo writing (See page 117). The chapter also included IS audit labor cost minimization theory proposed to answer the research questions. Chapter 5 will discuss the findings, limitations of the research, proposed recommendations, implications, and conclusion.

CHAPTER 5: FINDINGS AND RECOMMENDATIONS

The purpose of this qualitative study was to establish how the use of data analytics in the IS audit process can help to minimize labor costs and improve efficiency. In addition, the goal of this research was to explore perceptions of IS audit practitioners on the value of data analytics in the IS audit process. The problem explored in the study was that IS audits are not being completed in a timely and cost-effective manner to meet regulatory requirements (Oussii & Boulila Taktak, 2018). This is based on the theory that repetitive tasks in the IS audit process present an opportunity for organizations and audit teams to leverage data analytics to minimize labor costs and improve efficiency. Therefore, if organizations and IS audit teams can develop a suitable data analytics framework and provide advanced analytics training tailored to auditing, then they can improve efficiency and minimize audit labor costs.

The researcher collected survey responses from 27 ISACA members who hold any of ISACA's certifications in order to accumulate the data necessary to achieve the purpose of this qualitative research. The responses gathered helped the researcher to construct the digital labor cost theory through the implementation of Charmaz's (2014) grounded theory methodology. This theory establishes a better understanding of how the use of data analytics in the IS audit process can help to minimize labor costs and improve efficiency. According to 74% of participants' responses, 20 to 50% of tasks of the IS audit process are analytical and repetitive and could be automated. The other key factors cited by participants were establishing in-house analytics competency, reducing specialist engagements, automating complex manual tasks, implementing analytics guiding framework, and providing data analytics training. Like Kokina, Julia, and Davenport

(2017), many participants cited the use of artificial intelligence (AI) automation on certain manual repetitive tasks as the best way to reduce labor costs using data analytics.

One critical finding is that the use of data analytics has the potential to both minimize labor cost and reduce risk: the very reason for organizations to invest in audits. Future quantitative research could help establish certainty on the possible gains from data analytics. There are internal and external regulatory requirements that drive the audit function, and risk management is considered one of the key goals of IS auditing (Raiborn, Butler, Martin, & Pizzini, 2017). This study shows that IS audit projects that engage specialists allocate 10% to 35% of their budget to paying for specialist services; therefore, eliminating specialists by training internal staff and automating repetitive tasks could potentially minimize labor cost.

Limitations

The limitations of this study include the recruitment of participants and the assumption that participants are objective and truthful in their responses. Some members of ISACA do not hold any certifications. There was no mechanism to eliminate responses from uncertified members claiming to hold the required ISACA certifications. Another limitation is that some participants had never been involved in project labor decisions. Some participants had no knowledge of the existing IS audit process framework and some specific requirements of SAS No.56. Varying business regulatory environments for audit practitioners from different countries and regions also created a gap in internal control requirements for IS audits.

A general limitation of the qualitative study was that the volume of data collected made the constant comparative analysis and interpretation time-consuming. Limiting the sample size to 27 participants also affected the generalizability of the findings of the study considering the ISACA LinkedIn group and member support sites have over 189000 members. Overall, qualitative research results are difficult to verify and investigate for causality (Burrough, Baum, & Schwartz, 2019). The major limitation was participants expressed their opinions which may need to be validated through some future quantitative studies.

Findings and Interpretations

The participants' comments in this study provided an understanding of how the use of analytics techniques in the IS audit process could help to minimize labor costs and improve efficiency. About 67% of participant comments reiterate Oussii and Boulila Taktak's (2018) claim that IS audits are not being completed in a timely and cost-effective manner to meet regulatory requirements. This study offered several important contributions, closing an existing gap in literature. No prior scholarly work has set out to understand whether the use of data analytics in the IS audit process to reduce labor costs and improve efficiency. Findings from this study are consistent with the agency theory problem of the possibility of a misalignment of attitudes towards risk between the principal and the agency. In the case of specialist engagements, the principal, which is the hiring organization, may lack the ability to verify to what extent the agent behaved in the interests of the principal (Eisenhardt, 1989). When the principal has data analytics knowledge, the specialist is likely to behave in the interest of the company (Bosse & Phillips, 2016). Therefore, IS audit teams with data analytics training and knowledge may be better positioned to supervise specialists or carry out audits without involving external help. The outcome of having an IS audit team with data analytics knowledge may result in reduced audit cost.

Results from the analysis also suggest the use of automation based on data analytics may minimize labor cost and consequently have a beneficial effect on efficiency. The potential to impact the IS audit process was summarized by digital labor which came up as the main theme. Digital labor, in this context, referred to data analytics, RPA, and AI. The results also highlighted that a data analytics framework has the potential to contribute significantly to reducing IS audit labor cost through standardization and simplified process. Comments from participants suggested establishing in-house data analytics expertise in IS audit teams could reduce specialist engagements thereby helping organizations minimize labor costs.

Another notable finding reveals IS auditors perceive complex manual repetitive tasks and engagement of data analytics specialists on IS audit projects as potential cost drivers. However, comments from participants suggested automation through RPA, AI, and data analytics may help eliminate manual repetitive tasks. Other responses from participants suggested training internal staff on data analytics skills may also aids in minimizing use of costly specialist external labor.

A high-level description of the findings of this study was framed into a theory to help understand the possible benefits of using data analytics in the IS audit process. The grounded theory - IS Audit Labor Cost depicted in figure 14 emerged from the analysis of questionnaire responses. The findings from this study addressed the following three research questions:

RQ1: How can the application of data analytics in information systems (IS) audit improve the IS audit process?

RQ2: Can the cost of labor be lowered in information systems (IS) audit by utilizing data analytics?

RQ3: How could the use of data analytics framework improve IS auditing?

Findings for three research questions were based on the results from the questionnaire responses.

Research Question 1

How can the application of data analytics in information systems (IS) audit improve the IS audit process? The findings for RQ1 were to reduce audit team sizes by automating manual tasks with data analytics and to minimize time to answer audit questions by automating audits. In summary, 81% of the participants recommended adopting data analytics to simplify audit data analysis and quick identification of exceptions.

The first finding highlighted manual repetitive tasks as the key driver of IS audit teams triggering higher labor cost. Most respondents reported they work with teams composed of five to ten members or even more. Some of the tasks identified in many responses were sample selection and testing which can be automated using data analytics.

The second finding stemmed from insights offered by many of the respondents who claimed engaging data analysts and data scientists reduces time required to answer compliance questions. Although there is proven evidence of increased project cost when engaging data analysts and data scientists on IS audit projects, it was inferred in the participants' responses that the time to answer compliance questions is reduced. The time taken by most IS audit teams to carry out audits contributes to project expenditure given that many of the respondents said the percentage of data analysis related tasks constituted 20% to 50% of their project time.

Research Question 2

Can the cost of labor be lowered in information systems (IS) audit by utilizing data analytics? For RQ2, most respondents claimed hiring specialists increases labor cost on IS audit projects and constitutes 15% to 35% of project cost. The first key finding on RQ2 was that in-house predictive analytics improve process efficiency and effectiveness which in turn reduces project cost. In addition to efficiency and effectiveness, 48% of respondents said in-house predictive analytics could help quickly identify problems and risks which reduces costs.

The second finding was that training internal team members on advanced data analytics such as predictive analytics and artificial intelligence may help minimize the number of specialists hired on IS audit projects. 85% of respondents cited training and data analytics-based automation as critical factors to minimizing the number of data analysts and scientists engaged. Other benefits of deploying data analytics use in the IS audit process included bringing anomalies and hidden knowledge to the surface.

A third finding supported by 89% of respondents cited automation through artificial intelligence, robotic process automation, and data analytics as essential to accomplishing more IS audit tasks with fewer resources. Conventional manual IS audit process data analysis techniques are becoming obsolete due to increasing data set sizes (Pauley, Todd, Baldwin, & Dietrich, 2015). Internet of Things (IoT) has been contributing much to increasing data set sizes given the heavy use of sensors in most enterprise environments (Mandula, Parupalli, Murty, Magesh, & Lunagariya, 2015). Part of this finding included the use of RPA based on data analytics as another possible way to lower costs.

Research Question 3

How could the use of data analytics framework improve IS auditing? For this research question, most respondents referenced improved compliance, cost reduction, and IS audit process efficiency improvements as possible benefits of having a data analytics framework in the IS audit process. The first finding on compliance improvement recommended process standardization as another practical way to reduce risk and improve efficiency. A framework is cited to help establish a structure, policies, and procedures on how to use data analytics on IS audits. According to Jones, Ball, and Ekmekcioglu, (2008) an audit data framework is a valuable tool for gaining efficiency, savings, risk management, and cost reduction.

Study Taxonomy

This study strived to understand how the use of data analytics in the IS audit process may help to minimize labor costs and improve efficiency. In the process of conducting this study, the researcher established a taxonomy of features to illustrate the seven categories that emerged. A taxonomy is defined as a system categorizing multidisciplinary, complex phenomena into a set of common conceptual classes (Bradley, Curry, & Devers, 2007). This is usually done to increase clarity during constant comparative analysis when defining complex phenomena (Valentijn, Boesveld, Van der Klauw, Ruwaard, Struijs, Molema, & Vrijhoef, 2015). The taxonomy generated from this study provides a development agenda toward building a systematic framework for lowering IS audit labor costs and improving efficiency.

The grounded theory - IS Audit Labor Cost shown in Figure 14 distinguishes four dimensions that play inter-connected roles in establishing the level of labor cost and efficiency. The resulting IS digital labor cost theory provides a set of general propositions that helps explain and interpret how data analytics could be used to lower IS audit costs and improve efficiency. The dimensions are data analytics, repetitive tasks, training, and framework.

Data Analytics

A case study that surveyed 2100 CFOs on the importance of data analytics skills in auditing revealed that 61% of respondents agreed data analytics should be mandatory for everyone (Tschakert, Kokina, Kozlowski, & Vasarhelyi, 2016). They also claimed data analytics has the potential to produce higher-quality audit evidence, reduce repetitive tasks, and reduce risks. Tysiac (2015) said the issue with the use of data analytics is that sources of evidence have changed so much that the audit profession will have no choice but find ways to use it. In a related study, Earley (2015) argued that the use of data analytics on audit engagements has lagged in other areas but it holds great promise for the audit practice. Earley broke down data analytics concerns for the audit practice into three categories: (1) training and experience of auditors; (2) data availability, relevance, and integrity; and (3) expectations of the regulators and users. Regarding the training and experience of auditors, Barr-Pulliam, Brown-Liburd, and Sanderson, (2017) suggested the existence of big data sets could overwhelm the data processing capabilities of auditors.

Repetitive Tasks

A survey of 114 auditors from many accounting firms of all sizes by Payne and Curtis (2017) reveal that pressures of repetitive manual audit work and lack of education on the capabilities of available technologies form the two biggest obstacles to acceptance by auditors. A similar study by Tysiac (2015), interviewed James Comito who argued that the prospect of mechanization and automation raises potential job loss concerns for auditors. Comito further argued there are clauses in regulatory contracts that drive meaning from SOX and U.S. GAAP which a pure analytic may never be able to automate. Tschakert, Kokina, Kozlowski, and Vasarhelyi, (2016) proposed that any effort to advance the use of analytics in auditing should start by finding ways to reduce manual repetitive tasks.

Training

In research focused on the adoption of analytics in the audit practice, Earley (2015) listed the training and experience of auditors as one of the major opportunities of data analytics for IS auditors. Data analytic concerns in the audit community today entail competencies needed by auditors in big data environments, the need for the change of auditing standards, and the applicability of modern analytics in auditing (Vasarhelyi, Kogan, & Tuttle, 2015). Vasarhelyi, Kogan, and Tuttle, (2015) further argued educational needs must be met in areas such as IT, statistics, modeling, and machine learning techniques. Tysiac (2015) added that the best opportunity is by training younger auditors rather than attempting to convince veteran auditors to study computer vision and artificial intelligence.

Framework

An audit data framework can constitute an efficient guide for businesses to evaluate their big data for audit (El Arass, Tikito, & Souissi, 2018). El Arass, Tikito, and Souissi, (2018) contend an audit framework that incorporates data and analytics can enhance the adoption of data analytics in the IS audit process, but no research has yet looked at a possible framework. Riggins and Wamba (2015) proposed a framework to examine the adoption, usage, and impact on the internet of things as the first step toward formulating an audit data analytics framework to guide the IS audit process.

Recommendations

As previously stated, the objective of this qualitative research was to produce a finding that provide an understanding of how the use of data analytics in the IS audit process can help to minimize labor costs and improve efficiency. The digital labor cost theory is similar yet distinct from Huber's (1990) "Conceptual theory of the effects of advanced information technologies on organizational design, intelligence, and decision-making" that emphasizes the role of organizational design changes due to advanced technology (Cascio, & Montealegre, 2016). The digital labor cost theory is unlike Huber's process in that it focused on the "how" of a specific advanced technology (data analytics) whereas Huber's conceptual theory generalizes advanced technologies.

Huber's process included four constructs that started with "Availability of advanced information technologies ⟹ Use of advanced information technologies ⟹ Increased information accessibility ⟹ Changes in organizational design ⟹ Improvements in effectiveness of intelligence development and decision making" (Huber, 1990). In contrast, the goal of this study was not to establish the effects of advanced technologies on organizational design and decision-making. The goal of this study was to gain an understanding of IS audit practitioners' perceptions on how the use of data analytics could help lower labor cost and improve the efficiency of the process. Huber's process did not consider practitioner training on new technology and requirements for a framework to guide with integrating new advanced technologies into existing standards.

The ISACA membership community of IS auditors was the sample population for this study. To advance the use of data analytics in auditing, future researchers may consider increasing the sample size to more than 27 participants to cover the entire audit practice. The study focused on the significance of data analytics to lower labor costs and improve efficiency in the IS audit process due to the rapid expansion of data sets and IoT devices in enterprise environments. The accelerated adoption of IoT and big data technologies implementations to store and analyze large datasets created obstacles to timely audits and compliance (Elkhodr, Alsinglawi, & Alshehri, 2018; Giles, 2019). There are also assurance challenges associated with the old audit standards and frameworks not conforming to IoT requirements (Raphael, 2017).

The emergence of big data has compounded the efficiency and cost containment issues of the IS audit process (Dzuranin & Mălăescu, 2016; Zhang, Yang, & Appelbaum, 2015). Therefore, organizations may lower labor costs by reexamining the IS audit process to adjust the existing frameworks to accommodate new analytical techniques. Data analytics has the potential to reap great financial savings if it is well integrated into the IS audit process. In-house analytics training is the most efficient way to enhance the quick adoption of data analytics in the IS audit process (Tschakert, Kokina, Kozlowski, & Vasarhelyi, 2016).

Beyond just the core data analytics, process automation with robotic process automation and artificial intelligence was recommended by 52% of the respondents. Automation can help reduce manual repetitive tasks thereby lowering labor costs and improving efficiency.

Recommendations for Future Research

This study is a vital step toward establishing a foundation for understanding how the use of data analytics can transform the IS audit process. It sets a baseline for probing current gaps in the use of data analytics in IS auditing. Further research on development of a data analytics framework suitable for the IS audit process would help standardize the process and improve efficiency. The second recommendation would be to conduct a comprehensive study of the taxonomy of tasks within the IS audit process to distinguish manual, repetitive activities from those requiring human effort. The third recommendation would be to conduct a case study-based research that quantifies outcomes of real world IS audit projects leveraging data analytics. The fourth recommendation encourages future research to explore the significance of individual data analytics techniques like natural language processing, deep learning, and machine learning on the IS audit process. The fifth recommendation would be to explore research on changes that can be made to existing standards to enable the use of data analytics and other technologies relevant for automating IS audits tasks. The final suggestion for future research would be to explore case studies that measure the feasibility of including data analytics training in IS audit board of knowledge and education curriculums.

Chapter Summary

The purpose of this qualitative study was to understand how the use of data analytics in the IS audit process can help to minimize labor cost and improve efficiency.

In addition, this research sought to explore perceptions of IS audit practitioners on the value of data analytics in the IS audit process. The study findings demonstrated and established a framework that explains how the use of data analytics in the IS audit process can help lower labor cost and improve efficiency. The three research questions were the basis for the resultant findings. The researcher provided recommendations for IS audit leadership with a theory grounded in the perceptions of practitioners. Implementation of this research's recommendations has the potential to improve IS audit process, improve audit quality, minimize audit cost, and advance the audit profession.

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APPENDIX A: LITERATURE SEARCH

Key Word Search	Peer Reviewed Works Reviewed	Audit Practice Works Reviewed	Books Reviewed	Studies Reviewed
Information Systems Audit				
Key Theories	12	3	8	0
Audit Effectiveness	15	20	0	5
Audit labor & cost	28	18	0	6
Data Analytics Value				
General Data Analytics	25	6	2	1
Machine & Deep Learning	13	5	2	2
Audit Quality	12	2	0	0
Research Methodology				
Qualitative Analysis	20	12	3	8
Quantitative Analysis	11	5	0	3
Regulatory Compliance				
Audit and Analytics Technologies	5	3	0	3
Effectiveness	9	2	0	2
Total Documents Reviewed (271)	150	76	15	30

APPENDIX B: SURVEY INSTRUMENT

The survey instrument was administered on Google Forms, a publicly accessible and secure web site, https://docs.google.com/forms. The survey instrument had three sets of questions. The first set will carry the background of the study and establish informed consent of participants. The second set collected demographic information to ascertain participant age range minimum 18 or above to support consent considerations and confirm participants' ISACA membership, experience, certification, and job title to support validity of the study. The third set of questions will be used to capture IS audit practitioners' perceptions about the use of data analytics in the IS audit practice. Prior to conducting the survey, the survey instrument will first be validated by audit professionals, followed by a pilot study that validates the all components of the survey process. An additional fourth section will be included in the pilot survey only to collect feedback about the survey before the actual survey study is conducted. Content validation and pilot study details will be at the end of this appendix.

INTRODUCTION AND INSTRUCTIONS

The use of Data Analytics in Information Systems Auditing

Thank you for participating in this survey. This survey is an anonymous exercise conducted to aid research on the use of Data Analytics in Information Systems (IS) Auditing. This survey is part of a study that intends to establish if the use of data analytics in IS audit can lower labor costs and improve the audit process efficiency. The study hopes to provide a new understanding of the potential operational benefits of using data analytics in the IS audit practice. The survey is for all adults (18 or older) who are members of ISACA, employed or have experience in the audit field, and are certified in any of the following ISACA certifications CISA, CRISC, CISM, or CGEIT.
Participation is completely voluntary. There is no reward or payment for taking the survey. This study is for educational purposes only and will not publish any specific individual responses but just a summary of the findings without any respondent identifying information. Your participation in this study will consist of answering questions on the topics, and should take about 25 minutes on average.
When ready to proceed to the survey questions, click the NEXT button at the top left corner of this page. Please complete the survey in one session since the site is not designed to remember or partially save completed questionnaires.
Thank you so much for your time and assistance with this study.

Confidentiality and Privacy
The researcher will keep all the completed survey data confidential; data will be held offline at the end of the study. The researcher will release only analyses from the survey data. The researcher may allow future studies in IS audit to analyze the survey data, but purely for research work that maintains and guarantee the same confidentiality and privacy as this study.
The researcher has taken measures to protect your identity in the survey activity. There is no login or personally identifying information collected from participants. The survey starts with a few qualifying questions to confirm your eligibility based on the study's requirements. At the end of the survey period, all survey data will be saved offline. The survey process will not collect Internet (IP) address, which might identify participants. There will be no follow-up questions on survey responses. The researcher will not collect data about who took the survey.

Risk and Benefits of Participating
There is no risk to taking the survey. Your survey responses will not be shared with any employers, managers, or others. The survey is anonymous, and no respondent can be personally identified after completing the survey. Participants may benefit from being exposed to survey questions that elicit information about the value of using data analytics in auditing. Broadly speaking, the results of this study may benefit the broader audit community including consulting firms, clients, future researchers, and individuals in the audit practice. The study may be used to improve the IS audit process and frameworks.

Whom to Contact with questions about the study
To confirm that the study is an approved research activity of Capitol Technology University, you may contact:
The Office of the Dean of Doctoral Programs

Administrative Assistant Ms. Breana Anderson
bsanderson@captechu.edu

Tel: 240-965-2466

If you have any questions about the survey or study itself, please contact the researcher,

Leonard Manhanga
Ph.D. Candidate - Management and Decision Sciences
Capitol Technology University
Lmanhanga@captechu.edu

You are welcome to contact the researcher before or after completing the survey.

* Required

Informed Consent Agreement

Agreeing to Participate

Have you read the introductions, Confidentiality and Privacy, and instructions on how to go about this survey in the introduction statement? *

- ○ Yes
- ○ No

Do you agree that you are taking part in this survey voluntarily with no expectation of payment, and no penalty for not participating? *

- ○ Yes
- ○ No

Confirm Eligibility to Participate

Eligibility to Participate

Are you a vendor representing an auditing software company? *

- ◯ Yes
- ◯ No

Are you at least 18 years old? *

- ◯ Yes
- ◯ No

Are you a member of ISACA North-Texas Chapter and have auditing experience, and hold any of the following ISACA certifications: CISA, CISM, CRISC, or CGEIT? *

- ◯ Yes
- ◯ No

Please feel free to provide as much detail as you can in your responses to the questions below.

Audit Process Efficiency

* Indicates a mandatory question

1. Thinking back on your career in auditing, what can be done in the IS audit practice to help audit teams accomplish more tasks with fewer resources? *

Your answer

2. What has been the typical size range of your audit team(s) on different projects? *

Your answer

3. What types of data analysis do you conduct on your audits? *

Your answer

4. What percentage of your work time do you spend on data analysis? *

Your answer

5. How could you, your firm, or your client(s) benefit from engaging data analysts or data scientists on your audit projects? *

Please feel free to provide as much detail as you can in your responses to the questions below.

Audit Cost

* Indicates a mandatory question

1. What percentage of your IS audit project costs is typically allocated to hiring specialists? *

Your answer

2. What can be done in the IS audit process to minimize the number of specialists hired? *

Your answer

3. How does engaging specialists on IS audit projects affect project cost? *

Your answer

4. How could in-house predictive analytics improve IS auditing? *

Your answer

Please feel free to provide as much detail as you can in your responses to the questions below.

Data Analytics Framework

* Indicates a mandatory question

1. What changes if any should be made to the information technology assurance framework (ITAF) to pave the way for the use of data analytics in the IS audit process? *

Your answer

2. In what ways could a data analytics framework improve the planning and review of audits? *

Your answer

3. How could the introduction of a data analytics framework address SAS No. 94 requirements? *

Your answer

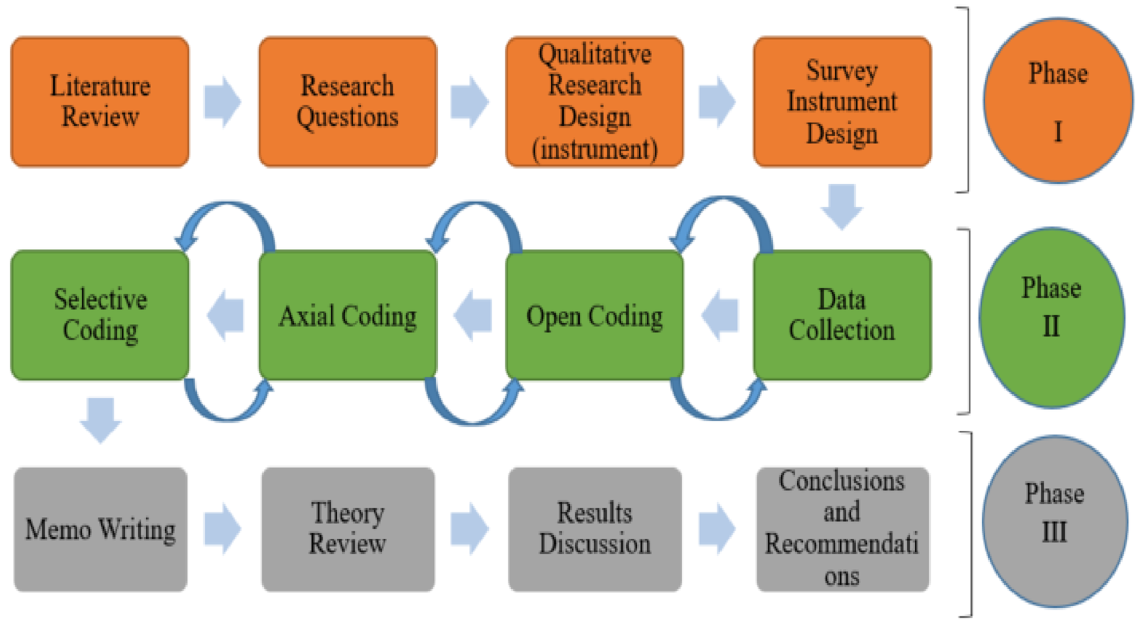
4. How could the use of data analytics in the IS audit process affect compliance with SAS No. 56? *

Your answer

SUBMIT

Never submit passwords through Google Forms.

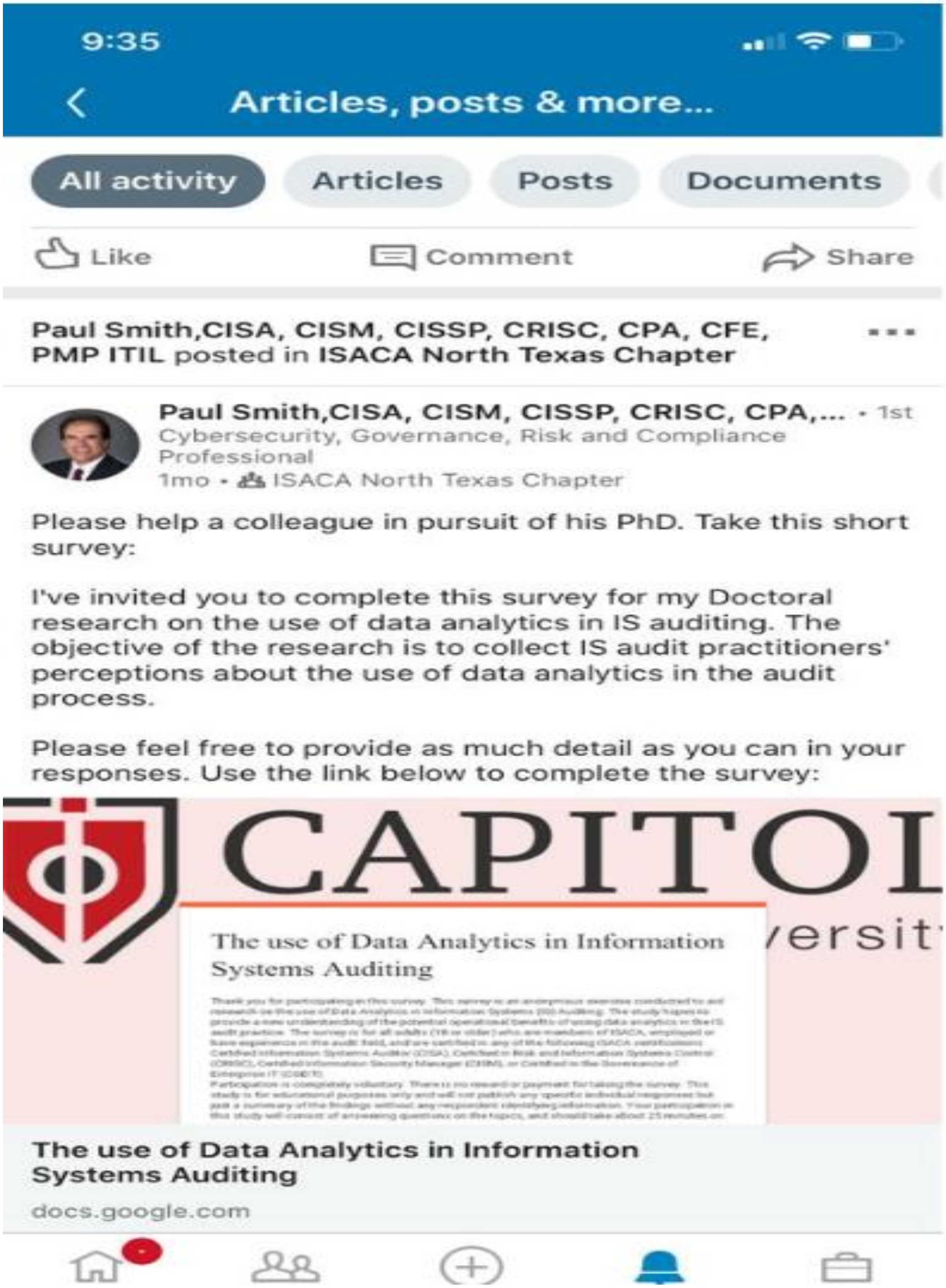
APPENDIX C: RESEARCH METHODOLOGY



Note: Derived from (Burden & Roodt, 2007), Figure 1: Implementing the grounded theory process.

APPENDIX D: LITERATURE MAP

APPENDIX E: PARTICIPANT INVITATION



APPENDIX F: NODE LISTING OF CODING REPORT

NODE LISTING OF CODING REPORTS

Total: 13 coding reports with 159 subcategories

Titles sorted alphabetically

Survey Questions

1. RQ1Q1. Accomplish more tasks with fewer resources (12 subcategories)
    - Align to budget
    - Automation - AI
    - Communication
    - Data analytics
    - Hiring practices
    - Planning
    - Prioritize
    - Risk management
    - Simplify audit methodology
    - Size of project
    - Tools - Agile
    - Training

2. RQ1Q2. Typical size range audit team(s) (4 subcategories)
    - 5 or less
    - 5 to 10
    - More than 10
    - NA

3. RQ1Q3. Types of DA on your audits (41 subcategories)
    - Accuracy
    - Application control reviews - high risk - high value
    - Bank reconciliations
    - CAATTS Analysis
    - Classification
    - Clustering
    - Comparisons - Testing (SOX, substantive, sample)
    - Completeness
    - Contract compliance
    - Data collection
    - Descriptive
    - Deviation detection
    - Diagnostic
    - Documentation for failed controls
    - Duplicate detections
    - Error rates in data

- General Ledger, AR and AP
- Integrity
- Inventory analysis
- Journal analysis
- KPI
- Link analysis
- Market
- Metrics
- NA
- None
- Payroll testing
- Predictive
- Purchasing to payment analysis
- Regression analysis
- Relevance
- Revenue line assurance
- Rule-based analysis
- Sales and production
- Sample selection - populations - stratification
- SoD checks
- Timeliness
- Travel and expense reporting
- Trends-based past performance - outliers
- Validations
- Vendors

4. RQ1Q4. Percentage of work time on DA (7 subcategories)
   - 05%
   - 10%
   - 20%
   - 30%
   - 40%
   - 50% or more
   - NA or none

5. RQ1Q5. Benefits data analysts on audit projects (19 subcategories)
   - Analyze outliers - understand themes
   - Audit planning
   - Best for financial audits
   - Confirm - validate
   - Continuous control monitoring
   - Data integrity and availability
   - Efficiency
   - Fewer resources
   - Hidden knowledge - data visibility
   - NA

- Not much - unneeded
- Objective results and outcomes
- Process improvement
- Reduces costs
- Risk-based focus
- Sample selection - population testing
- Scope of work
- Speed
- Use Tableau for analytics

6. RQ2Q1. Percentage audit costs hiring specialists (6 subcategories)
    - 0%
    - 10% or less
    - 15% - 35%
    - Entire budget
    - NA
    - Unsure

7. RQ2Q2. Minimize number of specialists hired (7 subcategories)
    - Hiring policies
    - NA
    - Process automation - data analytics
    - Retain experienced employees
    - Secondary school curriculum
    - Systems access - integrated programs
    - Training - Professional development

8. RQ2Q3. Specialists affect project cost (4 subcategories)
    - Cost containment
    - Increases cost
    - NA
    - Other

9. RQ2Q4. In-house predictive analytics improves (13 subcategories)
    - Confirm - validate
    - Efficiency - effectiveness
    - Identify problems & risks
    - Insight - knowledge
    - Lean and efficient organization
    - Planning - focus
    - Record time and skills
    - Reduces costs
    - Reduces work and man hours
    - Significantly improve
    - Special projects
    - Speed

- Unsure

10. RQ3Q1. Changes to ITAF use DA (5 subcategories)
    - Changes to framework
    - General purpose of using DA
    - Raise awareness - provide guidance
    - Sufficient now
    - Unsure
11. RQ3Q2. DA framework improve audit (10 subcategories)
    - Accuracy - completeness
    - Cost reduction
    - General benefit to company
    - Manage risk - compliance - security
    - More efficient
    - Planning - focus
    - Sample selection - population mining
    - Sufficient now
    - Time
    - Unsure

12. RQ3Q3. DA framework SAS No. 94 (19 subcategories)
    - Accuracy
    - Additional analysis
    - Availability of information
    - Complex calculations
    - Consistency
    - Data-focused approach
    - Documentation
    - Efficacy
    - Insights
    - IS Audit Universe
    - Issues relying on DA
    - Legislation - code of conduct
    - Monitoring
    - Objective results
    - Processing large volumes of data
    - Reduce audit procedures
    - Reduce risks
    - Timeliness of information
    - Unsure

13. RQ3Q4. DA compliance SAS No. 56 (12 subcategories)
    - Accuracy
    - Audit evidence
    - Consistency
    - Detect fraud

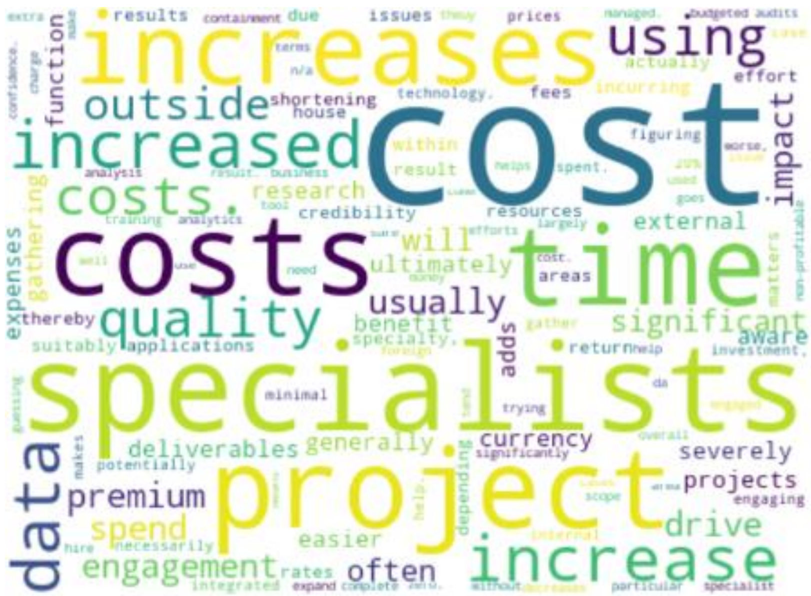
- Efficacy
- Increases need to comply
- Insights
- Objective results
- Overrides
- Planning
- Reduce audit procedures
- Unsure

APPENDIX G: CONCEPT EXTRACTION CODING REPORTS

RQ1Q1. Word Cloud for Concept Extraction - Thinking back on your career in auditing, what can be done in the IS audit practice to help audit teams accomplish more tasks with fewer resources?

RQ2Q2. Word Cloud for Concept Extraction - What can be done in the IS audit process to minimize the number of specialists hired?

RQ2Q3. Word Cloud for Concept Extraction - How does engaging specialists on IS audit projects affect project cost?



RQ2Q4. Word Cloud for Concept Extraction - How could in-house predictive analytics improve IS auditing?

RQ3Q1. Word Cloud for Concept Extraction - What changes if any should be made to the information technology assurance framework (ITAF) to pave the way for the use of data analytics in the IS audit process?

RQ3Q2. Word Cloud for Concept Extraction - In what ways could a data analytics framework improve the planning and review of audits?

RQ3Q3. Word Cloud for Concept Extraction - How could the introduction of a data analytics framework address SAS No. 94 requirements?

RQ3Q4. Word Cloud for Concept Extraction - How could the use of data analytics in the IS audit process affect compliance with SAS No. 56?