THREE ESSAYS ON THE ADOPTION AND APPLICATION OF EMERGING TECHNOLOGIES IN ACCOUNTING

by

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ABSTRACT OF THE DISSERTATION

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Technologies are evolving at an unprecedented pace and pose significant challenges and opportunities to the accounting and auditing profession. This dissertation consists of three essays that examine how emerging technologies can be accepted and adopted by auditors and managerial accountants.

The first essay attempts to incorporate the disruptive innovation concept (Christensen 1997) in understanding the adoption process of disruptive innovations in the audit domain. The essay defines sustaining and disruptive innovations from the auditing perspective and indicates that disruptive innovations can impact audit procedures at both the technology level and the methodology level. The disruptive innovations acceptance framework is then proposed to illustrate that sustaining innovations are adopted and developed within the audit practice, whereas disruptive innovations are developed by external parties. The disruption occurs when an emerging technology or methodology becomes accepted by audit regulations and adopted in audit practice. Further improvements on the adopted disruptive innovation become sustaining innovations.

The second essay aims at proposing the Contract Analytics Framework (CAF) to aid in the analysis of populations of perceived low-risk contracts. The essay identifies and describes six functional areas in the CAF framework: (1) Document Management; (2) Content Identification; (3) Cutoff Testing; (4) Record Confirmation; (5) Term Verification; and (6) Additional Audit Tasks. The CAF framework can be applied to audit tasks based on auditing standards, especially in the audit stages of risk assessment, substantive tests, and review. The framework is implemented on a group of reinsurance contracts to demonstrate the feasibility of auditing full populations of contracts.

The third essay proposes the Managerial Accounting Data Analytics (MADA) framework based on the balanced scorecard theory. MADA provides management accountants the ability to utilize comprehensive business analytics to conduct performance measurement and provide decision related information. With MADA, three types of business analytics (i.e., descriptive, predictive, and prescriptive) are implemented into four corporate performance measurement perspectives (i.e., financial, customer, internal process, and learning and growth) in an enterprise system environment. Other related issues that affect the successful utilization of business analytics within a corporate-wide business intelligence (BI) system, such as data quality and data integrity, are also discussed.

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CHAPTER 1: INTRODUCTION

Technologies are evolving at an unprecedented pace and pose significant challenges and opportunities to companies as well as the accounting and auditing professions. In the age of information explosion, numerous emerging technologies are being embraced by firms to make revolutionary changes in various industries and reshape business models. As professions closely related to company's business processes, accountants and auditors can be significantly impacted by emerging technologies. Therefore, it is of great importance to study how emerging technologies are adopted and implemented in accounting and auditing practice. This dissertation investigates this topic with three essays. The first essay focuses on the acceptance and adoption of sustaining and disruptive emerging technologies by auditors. The second essay aims at implementing natural language processing to assist auditors in performing effective and efficient contract analysis. The last essay concentrates on the adoption of data analytics by managerial accountants.

While certain technologies have been successfully accepted and adopted by auditors for cost reduction and audit quality improvement, auditors tend to be cautious and conservative when encountering other technologies (Manson et al. 1997; Alles 2015; Fischer 1996). Most of the previous research attempts to understand auditors' technologies adoption decisions through adoption models, such as the unified theory of acceptance and use of technology (UTAUT) model (Bierstaker et al. 2014; Curtis and Payne 2008; Janvrin et al. 2008a; Janvrin et al. 2008b). However, few studies have utilized disruptive innovation theory (Christensen 1997) to systematically examine how technologies are adopted by audit professions (Issa et al. 2016; Alles 2015).

The first essay attempts to provide the definition of sustaining and disruptive innovations in the audit domain and proposes the disruptive innovations acceptance framework to illustrate the distinct adoption process of sustaining and disruptive innovations by auditors. The definition of sustaining and disruptive innovations in audit domain is defined based on the concept of disruptive innovation proposed by Christensen (1997). A sustaining innovation in audit is defined as an improvement to a technology that is currently adopted in audit practice, whereas a disruptive innovation in audit is defined as a new technology or methodology that cannot be accepted by auditors in the first place, but, as it constantly improves, eventually has the potential to either displace current adopted technology or methodology. The definition is then applied to classify seven emerging disruptive technologies in auditing. The first essay then proposes the disruptive innovations acceptance framework to demonstrate that auditors are willing to accept and adopt sustaining innovations in audit practice, while reluctant to directly adopt disruptive innovations to perform audit tasks. Disruptive innovations are implemented and developed by external entities, such as the client firm's internal auditors, consultants, or emerging businesses. Audit regulations are modified to mandate or facilitate the adoption of a disruptive innovation when (1) the prevalent adoption of a disruptive innovation by the clients requires auditors to obtain a sufficient understanding of the innovation, (2) auditors begin to realize the benefits of efficiency and effectiveness brought by the disruptive innovation, and (3) the change of business environment request the adoption of disruptive innovation. Once a disruptive innovation is accepted and adopted in audit, any future improvement will become sustaining innovation. The first essay also utilizes the proposed framework to provide one potential reason for the lagged adoption of continuous auditing by external auditors.

Auditors use contracts extensively for risk assessment, analytical procedures, and substantive tests (PCAOB 2010b, 2010a, 2010e). Examining contracts for audit-relevant information can be associated with high cost, and auditors typically focus on significant or material contracts and utilize sampling techniques to examine large numbers of contracts associated with low perceived risk (AICPA 2008). However, samples are not always guaranteed to represent the full population accurately, and individual contracts with low risk may aggregate into a significant amount of risk (Teitlebaum and Robinson 1975; No 2019). While prior literature has examined improving methodologies on audit sampling (Dowling and Leech 2007; Messier Jr et al. 2001), the notion of auditing the entire population of textual documents, such as contracts, has not yet drawn the attention of researchers.

The purpose of the second essay is to propose an automated contract analysis framework that incorporates textual analysis to help auditors conduct effective and efficient audit analyses on full populations of contracts with low perceived risks. The proposed Contract Analytics Framework (CAF) consists of six functional areas: Document Management, Content Identification, Cutoff Testing, Record Confirmation, Term Verification, and Additional Audit Tasks. This essay also examines the current auditing standards in the audit stages of risk assessment, substantive tests, and review, and identifies audit procedures related to contracts that can be improved or automated utilizing the CAF framework. The CAF framework is illustrated on a small set of reinsurance contracts to assess its feasibility of generating audit evidence from the entire population of contracts. The results suggest that the proposed CAF framework can assist auditors in examining the full population of contracts and performing related audit tasks in an efficient and effective manner.

The role of management accountants has changed from historical value reporting to more real-time reporting and predictive reporting (Cokins 2013). Modern management accountants are involved in the business from four aspects: to participate in strategic cost management for achieving long-term goals; to implement management and operational control for corporate performance measure; to plan for internal cost activity; and to prepare financial statements (Brands 2015). Moreover, management accountants have successfully adopted and implemented enterprise systems to effectively and efficiently perform related tasks. However, studies indicate that the management accounting techniques have not changed significantly because management accounting principles and standards used by organizations prior to the implementation of enterprise systems have not changed. (Granlund and Malmi 2002; Scapens and Jazayeri 2003). To provide more relevant and valuable information to management in this highly technical business environment, management accountants should be further utilizing all of the functions of the enterprise system.

The third essay aims at discussing the potential impact of enterprise systems, big data, and data analytics on managerial accounting and proposing a framework that implements business analytics techniques into the enterprise system for measuring company performance using the balanced scorecard theory (Kaplan and Norton 1992). This essay first examines and discusses the impact of enterprise systems, big data, and data analytics on managerial accounting. The managerial accounting data analytics framework is then proposed for management accountants to utilize data analytics in the environment of enterprise systems. The framework applies descriptive, predictive, and prescriptive analytics to measure corporate performance from four aspects (i.e., financial, customer, internal process, and learning and growth). The analytical technique(s) selected by the accountant should not only be appropriate, but the data or big data selected for analysis should possess high-quality attributes such as relevance, timeliness, and accuracy, to ensure the usefulness of the information generated through the analytics.

The remainder of this dissertation is organized as follows. The three essays are incorporated in Chapters Two, Three, and Four. Chapter Five summarizes the findings and discusses the limitations as well as possible areas for future research of this work.

CHAPTER 2: TECHNOLOGICAL PROCESS REFRAMING THEORY: UNDERSTANDING TECHNOLOGY ADOPTION IN AUDITING WITH THE DISRUPTIVE INNOVATION CONCEPT

2.1 INTRODUCTION

Technologies are evolving at an unprecedented pace and pose significant challenges and opportunities to companies as well as the auditing profession. Innovations in technology such as Enterprise Resource Planning systems, artificial intelligence, Big Data analysis, and cloud computing are rapidly adopted by companies to obtain competitive advantages (Brynjolfsson and Mcafee 2017; Chen et al. 2012; Kallunki et al. 2011; Marston et al. 2011). Such emerging technologies like robotic process automation, artificial intelligence, and natural language processing are also having a profound impact on the auditing profession (Moffitt et al. 2018; Issa et al. 2016; Yoon et al. 2015). Thus, it is crucial for the practitioners and researchers in the audit field to understand the impacts, opportunities, and challenges associated with these technologies.

While auditors have successfully adopted certain technologies for cost reduction and audit quality improvement, they seem to be cautious and conservative when encountering other technologies (Manson et al. 1997; Alles 2015; Fischer 1996). Most of the literature attempts to explain this phenomenon by incorporating technology adoption models such as the unified theory of acceptance and use of technology (UTAUT) model from management information system research (Bierstaker et al. 2014; Curtis and Payne 2008; Janvrin et al. 2008a; Janvrin et al. 2008b). There are also some researchers pointing out the possible explanation through disruptive technology concept (Issa et al. 2016; Alles 2015). However, little research has been done to incorporate disruptive technology theory in analyzing technology adoption in the audit profession.

This essay attempts to expand the technological process reframing (TPR) theory proposed by Issa et al. (2016) through proposing a framework to illustrate the distinct adoption process of sustaining and disruptive technologies by auditors. Based on the concept of disruptive innovation proposed by Christensen (1997), this essay provides the definitions of sustaining and disruptive innovations within audit domain. A sustaining innovation in audit is defined as an improvement to a technology that is currently adopted in audit practice, whereas a disruptive innovation in audit is defined as a new technology or methodology that cannot be accepted by auditors in the first place, but, as it constantly improves, eventually has the potential to either displace current adopted technology or methodology, or change the audit procedures. Disruptive innovations can influence audit procedures at two levels, technology level, and methodology level.

Through the discussion of regulation and four factors (i.e., performance expectancy, effort expectancy, social influence, and price value) of technology adoption models, this essay concludes that auditors, in general, are willing to accept and adopt sustaining innovations in audit practice, while reluctant to directly adopt disruptive innovations to perform audit tasks. Therefore, sustaining innovations develops with the implementation experience and feedback from auditors, whereas disruptive innovations are implemented and improved by entities other than external auditors such as the client firm's internal auditors and consultants. As disruptive innovations constantly improve, regulators will gradually have the pressure to adopt them because: (1) the prevalent adoption of certain disruptive technology by the clients would require auditors to obtain a sufficient understanding of the technology; (2) the benefit of the disruptive technology becomes irresistible; and (3) auditors must adopt the disruptive innovation as the solution to generate relevant and sufficient audit evidence under the changing business environment. Regulation may be affected and eventually modified to mandate the adoption of the disruptive innovation. Once a disruptive innovation is adopted, any further improvements on the technology or methodology become sustaining innovations. This essay proposes the disruptive innovations acceptance framework that summarizes the adoption process of sustaining and disruptive innovations. The proposed framework can be used to provide one potential reason for the lagged adoption of continuous auditing by external auditors.

The contribution of this essay is twofold. First, this essay defines sustaining technology and disruptive innovations in auditing and classifies several emerging disruptive technologies based on their potential disruptive level. Alles (2015) suggests the possibility of using disruptive innovation theory to explain the adoption of data analytics in auditing and Issa et al. (2016) proposes the TPR theory and describes the potential improvements to audit procedures brought by the disruptive technologies. This essay adds to the TPR literature by providing explicit definitions of sustaining technology and disruptive technology in auditing. Second, the proposed framework illustrates the distinct processes how sustaining and disruptive innovations are adopted and impact the audit practice, which can be used to help researchers, audit practitioners, and regulators to understand the technology adoption in auditing. Prior literature that analyzes technology adoption by auditors focuses on technology adoption models such as UTAUT (Payne and Curtis 2008; Gonzalez et al. 2012; Curtis and Payne 2008; Janvrin et al. 2008a; Janvrin et al. 2008b; Bierstaker et al. 2014). This essay expands the literature in audit technology adoption research by incorporating the disruptive innovation theory.

This chapter is organized as follows: The ensuing section provides the literature review and the definition of sustaining and disruptive innovation in audit domain. The next section discusses disruption at technology and methodology level and classifies several emerging technologies. Next, factors impact the adoption of disruptive innovations are discussed and the disruptive innovations acceptance framework is proposed. The essay concludes by briefly expanding on suggestions for future research.

2.2 BACKGROUND AND LITERATURE REVIEW

2.2.1 Disruptive Innovations

The notion of "disruptive innovation" was first proposed by Christensen (1997) in his book "The innovator's dilemma: when new technologies cause great firms to fail." Christensen classified new technologies into two categories, sustaining and disruptive. Sustaining technologies refer to the technologies that foster improvements to the performance of established products, which is aligned with the value of mainstream customers in the major market. In addition, depending on the magnitude of the improvements, sustaining technologies can be further classified as discontinuous or incremental (Christensen 1997). Most new technologies belong to the sustaining category.

Disruptive innovation, on the other hand, refers to the innovation that initially leads to an underperforming product for an emerging market but eventually surpasses the established products and disrupts the entrenched market (Christensen and Raynor 2003; Christensen 2006).

Disruptive innovation demonstrates its character in a process rather than at a single point of time (Christensen 1997; Christensen and Raynor 2003; Yu and Hang 2010). In an established market, incumbent firms, in general, continuously develop and implement technologies to improve their product's performance and satisfy the customers in the market. When an entrant firm that supports the disruptive technology attempts to enter the market, it provides products that do not meet the minimum requirements or performance metrics valued by customers in the mainstream market (Danneels 2004). Such products are offered at cheaper prices to customers in the niche market, which is often ignored by the incumbent firms due to the low-profit margin. Over time, with more investment made into research and development, the disruptive technology gradually becomes mature. The entrant firm then is able to provide products not only satisfy the mainstream customers' requirement, but also cheaper, simpler, smaller, and more convenient to use. The incumbent firms are able to maintain competitive advantages in the high-end product by developing sustaining innovations. However, they will gradually lose interest from the mainstream market because the products offered are exceeding the customers' needs and at high prices. Eventually, the disruptive technology displaces the sustaining technology with entrant firms replace the incumbent firms (Yu and Hang 2010). Once the disruption process is completed, the mainstream market values are redefined, and further developments in disruptive technology occur in the way of sustaining technology (Christensen 1997).

Christensen (1997) states that because of the initial low profitability and uncertainty in the market associated with disruptive innovations, attempts to develop disruptive technologies with traditional management method would almost always lead to failures. He proposes that the successful management of disruptive technologies should include the following principles: 1) place projects to develop disruptive technologies in separate and independent organizations small enough to focus on small achievements; 2) plan to have inexpensive failures during the early stage; and 3) focus on finding the right market for the current attributes of the technology rather than relying on technological breakthroughs to enter the established market.

Disruptive innovation concept has been successfully applied to analyze new business models and technologies in various fields such as healthcare, lodging, taxi, education, and electronic device (Krotov and Junglas 2008; Christensen et al. 2011; Christensen et al. 2015; Guttentag 2015; Hwang and Christensen 2008). However, limited literature has implemented the disruptive innovation concept to examine technology acceptance by audit professions. Issa et al. (2016) discuss the immediate application of several AI-based technologies to the audit process and propose the Technological Process Reframing (TPR) theory, which is defined as “the reconsideration of methods and processes on an area of endeavor consequent of the advent of a disruptive technology.” However, this paper did not provide the explicit definition of disruptive technology and illustration of the distinct processes of auditors adopting sustaining technologies and disruptive technologies.

2.2.2 Definition of Disruptive Innovation in Auditing

Audit evidence is defined as "all the information, whether obtained from audit procedures or other sources, that is used by the auditor in arriving at the conclusions on which the auditor's opinion is based …." in Auditing Standards No.15 (PCAOB 2010e). Auditors evaluate audit evidence by sufficiency (i.e., quantity) and appropriateness (i.e., quality), where the appropriateness is further determined by relevance and reliability (PCAOB 2010e). Audit evidence is obtained through seven audit procedures, namely inspection, observation, inquiry, confirmation, recalculation, reperformance, and analytical procedures (PCAOB 2010e). Prior literature points out that technologies can significantly impact audit evidence and further develop new forms of audit evidence such as videos, social media, alarms and alerts, and so on (Moffitt and Vasarhelyi 2013; Vasarhelyi et al. 2015; Yoon et al. 2015; Brown-Liburd and Vasarhelyi 2015; Byrnes et al. 2018).

This essay provides the definitions of sustaining and disruptive innovations in audit domain based on the consideration of audit evidence and the audit procedures. Specifically, a sustaining innovation in audit is defined as an improvement to a technology that is currently adopted in audit practice. Sustaining technologies in general lead to straightforward enhancements that can be easily accepted by auditors because the technologies have very limited interference with the current mainstream audit methodology and procedures. A disruptive innovation in audit is defined as a new technology or methodology that cannot be accepted by auditors in the first place but, as it constantly improves, eventually has the potential to either displace current adopted technology or methodology or change the audit procedures. Auditors usually have reluctance to adopt a disruptive innovation at first sight because either its implementation cost largely exceeds the benefit, or it is not supported by the regulations (i.e., auditing standards). Hence, disruptive innovations are usually developed by entities other than auditors such as internal auditors, consultants, or researchers. As disruptive innovations constantly improve and are implemented by more client companies, the adoption cost for auditors would decrease and regulators would gradually encounter the pressure to modify the requirements to better suit the situation. Eventually, when a disruptive innovation is adopted, it will displace certain current technology or methodology, because the innovation can produce audit evidence with higher quality (i.e., effectiveness) or lower cost (i.e., efficiency). One particular character of disruptive innovations is their unpredictability. It is almost impossible to predict technological development, the success and failure of entrant firms, or the time of the occurrence of disruption (Christensen 1997). Thus, rather than predicting whether the emerging technology or methodology in audit will be a disruptive innovation, this essay identifies whether the aforementioned innovation contains the specific disruptive character that could potentially displace current audit evidence or audit procedures. The disruptive innovations mentioned hereafter essentially refers to "potential" disruptive innovations.

Disruptive innovations can influence audit procedures at two levels, technology level and methodology level. The technology level disruption can occur by replacing technologies adopted for current audit procedures or creating new types of audit procedures that generate different forms of audit evidence. When increasing number of technology level disruptions transpire in client firms and audit practice, disruptive innovations at methodology level would occur and change the fundamental of audit procedures, as well as the obtained audit evidence. The classification of sustaining and disruptive innovation is dynamic because once the disruption takes place, a disruptive innovation is adopted into the mainstream audit practice and any further development becomes sustaining.

2.2.3 Technology Acceptance and Adoption by Auditors

The development in technologies such as information systems has significantly impacted the business performance over the last few decades (Powell and Dent-Micallef 1997). Innovations in technologies such as Enterprise Resource Planning systems, artificial intelligence, Big Data analysis, and cloud computing are rapidly adopted by the companies to obtain competitive advantages (Brynjolfsson and Mcafee 2017; Chen et al. 2012; Kallunki et al. 2011; Marston et al. 2011). Serving the roles of providing reasonable assurance over the clients' financial statements (PCAOB 2015), auditors must acquire sufficient understanding of the client firms' business process, including technology innovations. In addition, adopting new technologies in audit procedures can benefit auditors by reducing workload, improving audit efficiency and effectiveness, and enhancing the reliability of audit work (Curtis and Payne 2008).

Various technologies have been proposed by researchers to improve audit efficiency and effectiveness. Appelbaum and Nehmer (2017b) present a framework to automate certain audit functions such as inventory inspection by utilizing unmanned aircraft systems (i.e., drones). Robotic process automation can assist auditors to perform repetitive manual tasks in revenue reconciliation and internal control testing (Moffitt et al. 2018). Vasarhelyi and Halper (1991) propose the idea of generating audit evidence through continuous measuring and monitoring of corporate systems and establishes the concept of continuous auditing, which can be adopted as the essential component of future audit (Dai and Vasarhelyi 2016). Dai and Vasarhelyi (2017) propose an accounting ecosystem based on blockchain to enable real-time monitoring and verification. Researchers also focus on developing audit data analytics to incorporate a variety of machine learning and artificial intelligent based methods, such as clustering, process mining, textual analysis, predictive analysis, exogenous variable prediction, Big Data, and visualization (Thiprungsri and Vasarhelyi 2011; Jans et al. 2014; Humpherys et al. 2011; Issa and Kogan 2014; Yoon et al. 2015; Vasarhelyi et al. 2015; Ngai et al. 2011). In addition, development in the commercialized software such as Caseware IDEA, Audit Command Language (ACL), and Tableau, decreases the level of prerequisite knowledge to utilize technologies and enables auditors to incorporate data analytics in audit processes with lower implementing cost.

However, despite the growing attention to advanced technologies paid by business and academia, the audit profession seems to be cautious and conservative in adopting new technologies (Manson et al. 1997; Alles 2015). Most of the literature attempts to explain this phenomenon by incorporating the technology adoption model such as the unified theory of acceptance and use of technology (UTAUT) model from management information system research (Bierstaker et al. 2014; Curtis and Payne 2008; Janvrin et al. 2008a; Janvrin et al. 2008b). Venkatesh et al. (2003) propose four significant direct determinants for user acceptance of technology in the UTAUT model: (1) performance expectancy, user expectation of performance improvement by using the system; (2) effort expectancy, user perceived degree of ease of using the system; (3) social influence, user perceptions of whether important others encourage the system usage; and (4) facilitating conditions, user expectation of organizational and technical infrastructures to support the system usage. Curtis and Payne (2008) conclude that auditors' technology adoption can be significantly impacted by factors including performance expectancy, effort expectancy, social influence, individual difference, and budget constraints. Nevertheless, there is limited literature studying audit technology adoption from the perspective of disruptive and sustaining technologies. This chapter attempts to expand the audit technology adoption research taking into consideration the disruptive innovations concept.

2.3 IMPACT OF DISRUPTIVE INNOVATIONS ON AUDIT

2.3.1 Disruption at Technology Level

Researchers propose that auditors can benefit from incorporating technologies in audit procedures (Bierstaker et al. 2014). Auditors can adopt a disruptive technology that will affect audit procedures in two ways. First, auditors can implement a disruptive innovation to replace certain technologies in current audit procedures. The main driving factor for such implementation is the substantial improvement in efficiency brought by the new technology. For example, auditors can replace several manual based techniques by utilizing robotic process automation to perform repetitive and low-judgment audit tasks (e.g., bank account confirmation) (Huang 2019) and employing drones to conduct inventory counts in a large warehouse or open-air inventories (Appelbaum and Nehmer

2017b). Undeniably, one critical assumption for such disruption to occur is that the implementation cost of the new technology should not exceed the benefit brought by efficiency improvement. Alternatively, some technologies disrupt audit by facilitating new types of audit procedures. Under this approach, auditors utilize the new technologies to obtain audit evidence through methods or data sources that are not available previously. For instance, applying process mining allows auditors to examine the event logs of transactions to identify possible anomalies (Chiu and Jans 2017; Jans et al. 2013). The obtained audit evidence can be regarded as new forms of audit evidence as described by (Moffitt and Vasarhelyi 2013). However, for auditors to accept the new audit procedures and new forms of audit evidence, regulations must evolve first to realize the demands for the corresponding level of assurance.

2.3.2 Classification of Several Disruptive Emerging Technologies in Auditing

Seven disruptive emerging technologies that can be implemented in auditing are classified based on how they can affect audit procedures in Table 1.

Table 1: Classification of Several Emerging Technologies

Disruptive Emerging Technology	*Current Audit Procedures*	*New Audit Procedures*
Blockchain and Smart Contract		√
Interactive Data Visualization	√	√
Machine Learning	√	√
Natural Language Processing	√	√
Process Mining	√	√
Robotic Process Automation	√	
Unmanned Aerial Vehicle (Drones)	√	

Blockchain and Smart Contract

Blockchain provides a secure infrastructure for transactions between unfamiliar parties without the central authority by establishing a decentralized public ledger. The technology can serve as a foundation to enable automatic assurance and bring more agile and precise to current auditing paradigm (Dai and Vasarhelyi 2017). Wang and Kogan (2018) propose the Blockchain-based transaction processing system (Bb-TPS), combined with zero-knowledge proof, that allows auditors to perform analytic procedures on real-time transactions while preserving confidentiality. Specifically, through Bb-TPS, auditors can verify the accuracy and integrity of transactions in real time without knowing the actual numbers. Also, combining blockchain technology and smart contracts together provides a feasible solution for efficient implementation of continuous auditing (Rozairo and Vasarhely 2018; Appelbaum and Nehmer 2017a). Appelbaum and Nehmer (2017a) state "[i]n a Blockchain and continuous evidence collecting environment, these more technical audit procedures stand in contrast to the earlier traditional approaches." Thus, it is difficult for auditors to directly implement blockchain in current audit procedures. However, blockchain has the potential to establish new audit procedures by providing auditors the ability to audit real-time transactions and maintain confidentiality (Wang and Kogan 2018). In addition to disruption in technology level, blockchain also has the capability to disrupt at methodology level. Dai and Vasarhelyi (2017) propose that blockchain could enable a real-time, verifiable, and transparent accounting ecosystem and create a more precise and timely automatic assurance system. Such disruption would change the fundamentals of audit processes and impact all audit procedures.

Interactive Data Visualization

Data visualization is defined as "the use of computer-supported, interactive, visual representations of data to amplify cognition, or the acquisition and use of knowledge" (Card 1999). Interactive data visualization (IDV) consists of three elements: interaction, selection, and representation. Interaction refers to the decision maker's communications to the system to explore data and discover new insights. Selections involve choosing a subset of data from large or complex data sets for display. Representation refers to the display of data on a computer, whether in text or a variety of graphical formats (Dilla et al. 2010). Prior literature shows that IDV tools allow users to be more likely to consider multiple factors, facilitate more compensatory processing strategies, and leading to more accurate decisions (Lurie and Mason 2007). Interactive data visualization has been applied to analyze data produced by ERP systems and identification of fraudulent activities (Dilla and Raschke 2015). Auditors can benefit from IDV in two ways. Firstly, IDV provides auditors the ability to better understand the client's data, which improves the efficiency and effectiveness of current audit procedures. From this perspective, IDV is considered as a sustaining innovation that enhances the technologies adopted in current audit process. Secondly, IDV has the potential to assist auditors in adopting data analytic techniques by making the result of data analytics easier for auditors to understand and analyze (Dilla and Raschke 2015). Liu et al. (2019) propose a framework for auditors to adopt IDV not only as a technique to obtain better understanding of large size financial data, but also as a method to perform exploratory data analysis (Liu 2014). As a result, IDV can both disrupt visualization technologies adopted in current audit procedures and enable the potential of new audit procedures.

Machine Learning

Machine learning, as a subset of artificial intelligence, aims to use computer systems to learn from data, identify patterns, and make decisions with minimal human intervention (Bishop 2006). Accounting and auditing researchers are demonstrating a substantial interest in machine learning and have explored to apply machine learning in various fields such as fraud detection, bankruptcy prediction, going concern assessment, and financial condition forecasting (Wang 2010; Foster and Stine 2004; Anandarajan and Anandarajan 1999; Ding et al. 2008). Thiprungsri and Vasarhelyi (2011) apply cluster analysis to assist auditors filtering abnormal and suspicious life insurance claims and propose that clustering can be utilized for automate fraud filtering during an audit. Machine learning can also be incorporated by auditors in the form of audit support system or expert system (Sutton et al. 2016). Additionally, one major application of machine in audit is through audit data analytics. Audit Data Analytics (ADA) is defined as "the analysis of data underlying financial statements, together with related financial or non-financial information, for the purpose of identifying potential misstatements or risks of material misstatement" (Stewart 2015). ADA can be adopted not only to improve efficiency in current audit procedures, but also as a prospective solution for auditors to accommodate the environment where the client data is exhibiting large variety, high velocity, and enormous volume, or referred to as Big Data (Appelbaum et al. 2017). Consequently, machine learning is considered as a disruptive innovation that can improve current audit procedures, create new audit procedures, and bring methodology level revolutions to auditing.

Natural Language Processing

Natural Language Processing (NLP) is "theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications" (Fisher et al. 2016). NLP and text mining techniques have attracted the attention of academics and practitioners for their ability to extract useful information from unstructured text. Accounting researchers have shown that auditors can use NLP to flag questionable financial disclosures and assess fraud risk (Goel et al. 2010; Goode and Lacey 2011; Humpherys et al. 2011). Cecchini et al. (2010a) utilize

NLP to analyze Management Discussion and Analysis Sections to identify firms with potential fraud or bankruptcy. Researchers have suggested that text mining will be utilized by auditors to provide valuable complements to traditional audit evidence in the future (Yoon et al. 2015). Moreover, NLP can lead to improvements in management-control systems, budgeting processes, accounting-data quality, and the refinement of accounting standards in financial reporting (Warren Jr et al. 2015). NLP can also be used for auditors to perform full population test on contracts and documents as mentioned in the following chapter. These examples demonstrate that NLP can be adopted both as a disruptive technology for the audit procedures (e.g., document inspection) but also to create new types of audit procedures (e.g., obtain evidence from social media).

Process Mining

Process mining is a technique that extracts knowledge by analyzing event logs recorded by an information system (Jans et al. 2013). An event log is defined as "a chronological record of computer system activities which are saved to a file on the system" (Jans et al. 2014). Thus, process mining aims at analyzing the information that is automatically recorded by the firm's information technology system. Jans et al. (2013) argue that auditors should leverage the capabilities of process mining because: (1) process mining analyzes the full population of testing data rather than a sample; (2) process mining focuses on the event log data, which is recorded automatically by the information technology system and more independent from the actions of the auditee; (3) process mining provides ways to conduct walkthroughs and analytic procedures; and (4) process mining allows auditors to perform analyses such as identifying transaction processes that are not possible with existing audit tools. Specifically, process mining can be used as the audit tool for process discovery, conformance check, performance analysis, social network analysis, and decision mining and verification. Chiu and Jans (2017) apply process mining to analyze data from a large European bank to evaluate the effectiveness of internal controls and identify abnormal records. Thus, process mining can not only improve the efficiency of current audit tasks but also create new audit procedure to investigate the log information of transactions.

Robotic Process Automation

Robotic Process Automation (RPA) is defined by the IEEE (Institute of Electrical and Electronics Engineers) Standards Association as "[a] preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management'' (IEEE 2017). Specifically, RPA is defined by Aguirre and Rodriguez (2017) as "a software that is laid on top of the information technology infrastructure, connects separated process, and reproduces the manual work on computers." There are in general three attributes of RPA-appropriate tasks: (1) the processes to be automated should be well-defined; (2) more benefit can be obtained if the automating tasks are of high volume and repetitive; and (3) tasks should be mature, which the outcome and costs can be well predicted and measured (Lacity et al. 2015). RPA can be implemented in auditing for manual and repetitive tasks, including but not limited to reconciliations, internal control testing, and detail testing (Moffitt et al. 2018). The automation of repetitive manual work would help auditors to allocate more resources to audit areas with complex nature, reduce manual work cost, and eventually improve the audit quality. Because the current implementation of RPA aims at improving efficiency and lowering the cost of repetitive manual audit work, it is not generating any new type of audit evidence. Thus, RPA is considered as a technology that demonstrates its disruption at current audit procedures only. However, future development in RPA such as the integration with artificial intelligence provides RPA with the potential to be disruptive even at methodology level.

Unmanned Aerial Vehicle

Unmanned aerial vehicle (i.e., drones), are extensively used in infrastructure, agriculture, transport, security, media and entertainment, insurance, photography, mining, and natural science (PricewaterhouseCoopers 2016). Cameras, RFID trackers, sensors, and geo-location devices can be combined with drones to provide picture, video, and sensor feed. Appelbaum and Nehmer (2017b) suggest that auditors can use drones for evidence collection in physical inspection and observations. Specifically, drones can be utilized to perform evaluation, observation, inspection, and recounting of the physical inventory. In addition, this paper also proposes a framework to integrate drones in the continuous auditing environments through the automation of certain audit tasks (Appelbaum and Nehmer 2017b). The benefits of using drones to perform physical inspection include cost reduction and accuracy improvement, which are considered as a disruption of current audit procedures. However, drone technology has the potential to enable the methodology level disruption such as continuous auditing.

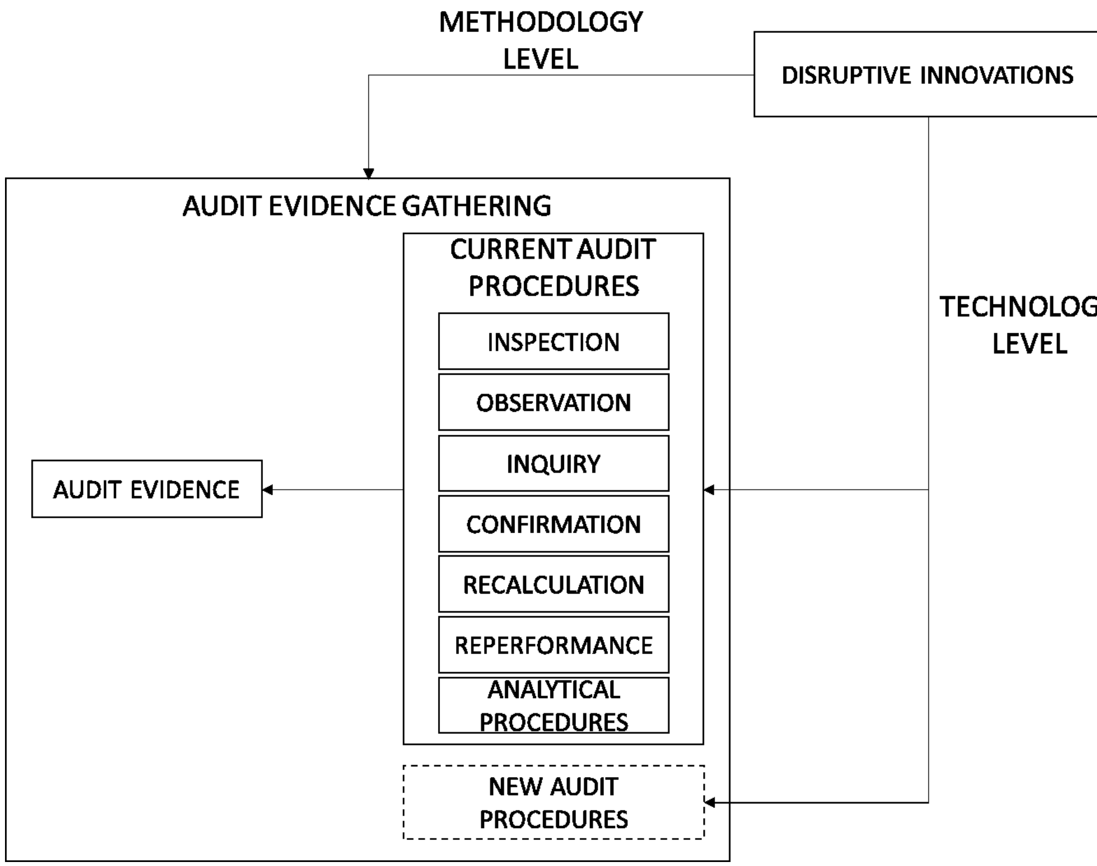
2.3.3 Disruption at Methodology Level

In addition to the technology level, disruptive innovations can also impact auditing at the methodology level. A methodology level disruptive innovation refers to a new type of audit methodology that could tremble the fundamentals of audit processes and impact or alter most audit procedures. This type of disruption must be initiated with changes in auditing standards because external auditing profession is highly bound by regulations. The major reason for such disruption to occur is that the evolving business environment diminishes the quality of auditing evidence obtained through current audit procedures, thus making the audit opinion less relevant and reliable. When a methodology level disruption transpires, regulators and auditors must redesign the audit procedures and processes to accommodate the transformation of business. Information Technology (IT) audit, which began as Electronic Data Process audit, can be viewed as one example of methodology level disruption as it was caused by increasing usage of computer systems and significantly affected the way for auditors to perform audit tasks (Davis 1968).

There are several emerging innovations that can lead to methodology level disruption. One typical example is continuous auditing. Continuous auditing is defined as "a methodology for issuing audit reports simultaneously with, or a short period of time after, the occurrence of the relevant events" (CICA/AICPA 1999). It is initially proposed as the Continuous Process Auditing System (CPAS) to execute automated, near real-time, analyses on the full population of records (Vasarhelyi and Halper 1991). Vasarhelyi et al. (2004) propose a theoretical framework for continuous auditing and define the concept of "audit by exception." The fundamental process of continuous auditing is utilizing predefined rules to continuously monitoring and evaluating transactions. Detections of rule violation will lead to alarms (i.e., exceptions) sent to auditors for further examination. Hence, the emphasis of audit work shifts from verifying the transactions to investigating the exceptions (Vasarhelyi et al. 2004). Compared with traditional audit techniques, continuous auditing can be deployed more frequently to obtain timelier and more relevant audit evidence. In addition, continuous auditing has the ability to perform full population testing, which may enhance the quality of evidence and lower audit risk (Brown et al. 2007). Continuous audit is providing a substantially different type of audit evidence by examining exceptions. Should continuous auditing is fully adopted in external audit, audit procedures must be redesigned so that auditors can obtain audit evidence from exceptions effectively and efficiently. Blockchain and data analytics can also lead to methodology disruption as Blockchain has the ability to create a transparent, verifiable, and tamper-resistant accounting system (Dai and Vasarhelyi 2017), while audit data analytics can be applied to analyze business transactions in the Big Data environment (Appelbaum et al. 2017; Appelbaum et al. 2018).

The process of how disruptive innovations can impact the generation of audit evidence at the technology level and the methodology level is summarized and demonstrated in the following Figure 1.

Figure 1: Disruptive Innovations at Technology Level and Methodology Level



2.4 AUDITOR ACCEPTANCE OF DISRUPTIVE INNOVATIONS

2.4.1 Factors that Impact the Adoption of Disruptive Innovations

This study focuses on two factors to discuss the adoption of disruptive innovations. The first and most important factor is regulation. External auditing is one of the professions that are strictly bounded by regulations (Appelbaum et al. 2017). It is required for auditors to conduct audit engagement in accordance with the Auditing Standards. Consequently, without support from regulators, disruptive innovations have very limited chance to be accepted and adopted by auditors. However, auditing standards are not immutable and should be constantly evolving to adapt the ever-changing business environment. Revolutions in business practice, especially those occurring in client firms, could put pressure on regulators to modify the standards to accommodate such changes. For example, Elliott (2002) states "[p]resent and future users of accounting and auditing services have increasing need for relevant, reliable, and timely information and IT provides the means to meet them." In addition, researchers have also been advocating the adoption of audit data analytics as an answer to Big Data (Liu and Vasarhelyi 2014; Vasarhelyi et al. 2015; Warren Jr et al. 2015; Yoon et al. 2015; Zhang et al. 2015; Cao et al. 2015; Appelbaum 2017; Appelbaum et al. 2017).

Under the extent of regulation support, which will most likely occur at the technology level, the second factor for adopting disruptive innovations lies in the consideration of technology acceptance and adoption models. The research in individual acceptance and use of information technologies has led to various information technology acceptance models such as technology acceptance model and unified theory of acceptance and use of technology (Venkatesh et al. 2003; Venkatesh and Davis 2000; Venkatesh et al. 2012). Researchers in auditing domain have applied such technology adoption theories to analyze auditors' attitudes and reactions towards computer-assisted audit techniques, technology implementation decisions, and adoption of continuous auditing (Bierstaker et al. 2014; Curtis and Payne 2008; Vasarhelyi et al. 2012). Using UTAUT as the fundamental theory of technology acceptance and combining previous literature in technology acceptance and adoption in auditing, this study proposes that auditor's acceptance of technologies can mainly be explained by four factors: performance expectancy, effort expectancy, social influence, and price value (Venkatesh et al. 2003; Venkatesh et al. 2012; Curtis and Payne 2008). The decision of whether adopting certain technologies in audit practice is made based on the comprehensive consideration of the four factors. Discussion on the four factors is formed based on two stages, the initial stage where a disruptive innovation is first proposed, and the disruptive stage where the proposed technology has been well developed for adoption.

Performance Expectancy

Performance expectancy refers to "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" in UTAUT (Venkatesh et al. 2003). Technologies may improve auditor's performance by reducing the number of working hours (i.e., efficiency) and increasing the accuracy and scope of audit procedures (i.e., effectiveness). For example, auditors can employ RPA to send and collect confirmations to all the banks where the client has accounts with spending fewer hours, as compared to sending the confirmations manually (Moffitt et al. 2018). The larger the performance improvement auditors are expecting, the higher probability the technology will be accepted and utilized in the audit practice. In the initial stage, the enhancements brought by a sustaining innovation to audit practice are based on the current adopted technology. Thus, auditors tend to have few difficulties in understanding the benefits bestowed by the sustaining innovation and have more precise estimation and measurement of improvements to current audit tasks. Alternatively, disruptive technologies provide improvements through introducing a new technology that has the potential to substantially outperform and eventually replace the current adopted technology. In other words, the benefits brought by the disruptive technology in the initial stage can be ambiguous and difficult for auditors to comprehend. Therefore, in the initial stage, auditors are likely to express high performance expectancy on sustaining innovations and low performance expectancy on disruptive innovations. As the innovation becomes developed and adopted by more clients at the disruptive stage, auditors will have more exposure and better understanding of such technology. Consequently, auditors will have a higher performance expectancy on the technology at the disruptive stage, as compared to at the initial stage.

Effort Expectancy

Effort expectancy is defined as the degree of ease associated with using the system (Venkatesh et al. 2003). Since auditors may not only make the decision of adopting a technology but also are responsible for the implementation of technology, the effort involved with adopting a technology may be more salient to auditors than other professionals (Payne and Curtis 2008). Even though auditors can sometimes rely on consultants or external third parties to implement a new technology, an adequate understanding of the technology is still required before auditors can use the result for audit tasks. Normally, the lower the effort associated with the technology implementation, the more likely the technology will be adopted (Venkatesh et al. 2012). Prior research also points out that the construct of effort expectancy is significant during the initial implementation and will become nonsignificant over the periods of extended and sustaining usage (Agarwal and Prasad 1997). When faced with a new technology, auditor's effort expectancy can be affected by factors such as system interface, result interpretability, and learning curve (Bierstaker et al. 2014). Although no general conclusion can be made regarding the quality of software systems of sustaining technologies and disruptive technologies, accepting a new technology would definitely mean more effort than accepting improvement in an adopted technology. Thus, auditors will have lower effort expectancy for disruptive innovations in the initial stage. As a disruptive innovation continuously develops in business practice, effort related factors such as system interface and result interpretability would also be enhanced, resulting in an increase in effort expectancy. Therefore, auditors tend to estimate a higher effort expectancy for a disruptive innovation at the disruptive stage.

Social Influence

Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the new system (Venkatesh et al. 2003). Prior literature finds that auditor's decision can be significantly different based on whether he or she is aware of the superiors' preference (Tan et al. 1997). Auditors can be influenced by the opinion from both inside and outside the audit team (Curtis and Payne 2008). In addition, staff auditors are more likely to use commonly available software than manual approaches when the supervisors support the decision (Loraas and Wolfe 2006). Sustaining innovations, due to the straightforward improvements on currently adopted technologies, are more likely to be supported by the auditor's colleagues and supervisors. Meanwhile, disruptive innovations may not have as much exposure among the audit team in the initial stage. Therefore, auditors will have more social support to adopt a sustaining innovation at the initial stage. However, in the disruptive stage, a rising social pressure for auditors to adopt a disruptive technology can result from both the audit team as well as client firms. The magnitude of the social influence from inside the audit team can be larger because auditors pay more attention to the opinions from colleagues and supervisors than the clients. Consequently, auditors have more social influence to adopt disruptive technologies at the disruptive stage than at the initial stage.

Price Value

Price value is defined as users' cognitive tradeoff between the perceived benefits of the technology and the monetary cost for using it (Venkatesh et al. 2012). Auditors are under significant pressure to maintain the budget while performing audit procedures. Curtis and Payne (2008) conclude that longer-term budget will smooth start-up costs for the technology adoption in the first year and increase the probability for auditors to accept the technology. The cost associated with adopting a new technology includes an initial implementation cost, followed by maintaining cost as the technology usage continues. Such costs are determined by the technical characteristics of the technology. For example, interactive data visualization may require a high initial cost to purchase the software but relatively low maintenance cost. Another factor auditors may consider is the potential risk in the future as auditors are expecting constant long-term benefit when deciding to implement a new technology. Hence, it may be not reasonable to estimate the price value associated with a disruptive innovation in the initial stage. However, auditors are more likely to obtain a certain understanding of the price value when they decide to implement a sustaining innovation to current adopted technologies. As a new technology improves to the disruptive stage, it is rational to assume its implementation cost, such as price of related commercial software, and the maintenance cost will decrease. In addition, the risk of future benefit will also decrease as the disruptive technology becomes more accurate and reliable. As a result, the price value of a disruptive technology is estimated higher at the disruptive stage.

Overall, this study proposes that, within the extent of regulation support, it is easier for auditors to accept a sustaining innovation than a disruptive innovation in the initial stage. Additionally, the adoption likelihood for a disruptive innovation will be higher at the disruptive stage as compared to the initial stage. The following two tables summarize the above discussion.

Table 2: Analysis of UTAUT Factors of Sustaining and Disruptive Innovations at Initial Stage

	Sustaining Innovations	Disruptive Innovations
Performance Expectancy	Higher	Lower
Effort Expectancy	Higher	Lower
Social Influence	Higher	Lower
Price Value	Certain	Uncertain
Adoption Decision	Higher	Lower

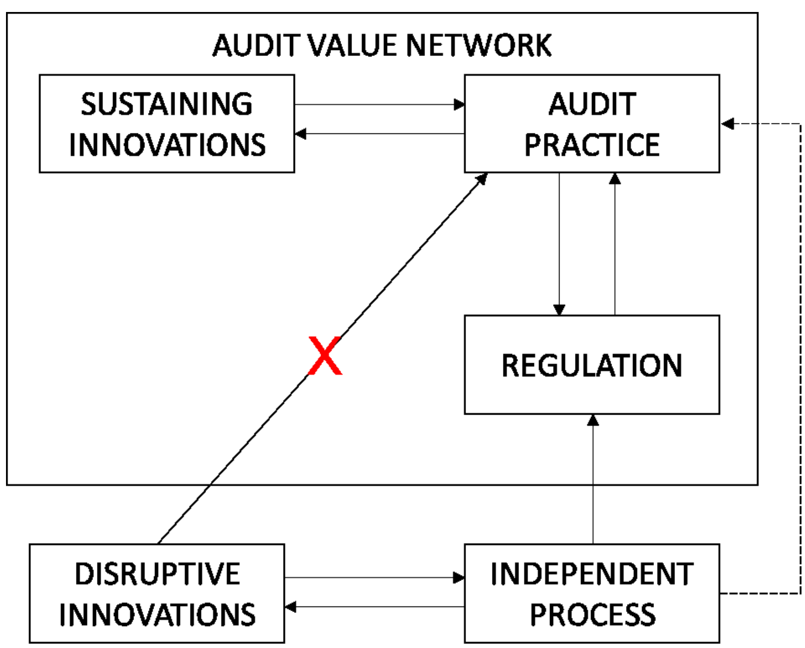
Table 3: Analysis of UTAUT Factors of Disruptive Innovations at Initial Stage and Disruptive Stage

Disruptive Innovations	Initial Stage	Disruptive Stage
Performance Expectancy	Lower	Higher
Effort Expectancy	Lower	Higher
Social Influence	Lower	Higher
Price Value	Lower	Higher
Adoption Decision	Lower	Higher

2.4.2 Disruptive Innovations Acceptance Framework

Christensen (1997) points out that companies are prone to accept and adopt sustaining innovations and reluctant to directly embrace disruptive innovations. The same idea can be applied to auditors. However, auditors have a higher barrier to accept disruptive innovations as support from regulation is required before the innovation can be adopted. Therefore, sustaining innovations are more likely to impact audit procedures and develop within the audit practice, whereas disruptive innovations impact mainstream audit practice from the outside of audit practice. The disruptive innovations acceptance framework, as shown in Figure 2, summarizes the process of how sustaining and disruptive innovations impact the audit practice and regulation.

Figure 2: Disruptive Innovations Acceptance Framework



Christensen (1997) defines a value network as “the context within which a firm identifies and responds to customers’ needs, solves problems, procure input, reacts to competitors, and strives for profit.” The “audit value network” in this essay refers to the context within which auditors perform audit procedures, obtain audit evidence, and generate audit reports under the influence from budget, regulations, and industry specified common knowledge.

Sustaining innovations are improvements over currently adopted technologies that can be directly accepted by auditors. Therefore, sustaining innovations are adopted and developed inside the audit value network. Auditors implement accepted sustaining innovations in current audit procedures with the expectation to improve accuracy, reduce cost, and enhance quality. The implementation experience and feedback would then be used to create a feedback loop which leads to further improvements and evolutions in currently adopted technologies. Occasionally, the impacts caused by a certain sustaining innovation can be so significant that auditors may need to alter the way to perform audit procedures to address the change. Nevertheless, no matter how significant the audit procedures may have been modified, the current adopted technology is not be affected, and thus the improvement is considered sustaining.

Disruptive innovations, in general, are almost impossible to be directly accepted and implemented by auditors due to the regulation factor and the technology adoption factor as discussed in the previous section. Therefore, disruptive innovations are adopted and implemented first by independent processes that are outside the audit value network. Client firm’s internal auditors and accounting department, as well as consultants from the audit firms, are all prospective adopters of disruptive technologies. As more enhancements and evolutions are made by parties outside the audit value network, some innovations will begin to demonstrate the disruptive ability to audit practice at two levels, the technology level and the methodology level. Technology level disruptive innovations impact audit procedures by replacing currently adopted technologies or creating new types of procedures, whereas methodology level disruptive innovations have the potential to change the fundamentals of all the audit procedures.

There are very few disruptive innovations that can be adopted by auditors without considering the regulation factor. Auditors won't adopt a disruptive innovation unless there is support or requirement from regulators. Disruptive innovations could pressure the regulation change through several aspects. Firstly, when a client adopts a disruptive technology that can significantly impact its financial performance, auditors must obtain a sufficient understanding of such technology to assess the associated risk. Once the adoption of such disruptive technology becomes prevalent among companies, regulators would gradually become aware of this technology and initiate designing regulations related to the technology. For example, the widespread using of radio-frequency identification (RFID) for inventory management would require auditors to understand the technology appropriately before they can rely on the result (Dai and Vasarhelyi 2016), which is highly likely to cause a modification in the regulations. Secondly, auditors are likely to demand regulation changes so that they can benefit from the higher efficiency and effectiveness brought by disruptive technologies. Disruptive technologies are likely to outperform current technology in most aspects but may incur significant implementation cost.

However, the adoption cost for auditors can be significantly reduced if most of the clients have already implemented the disruptive technology, and auditors can choose to rely on the result of the disruptive technology. Some auditors may voluntarily choose to experiment the disruptive technology in addition to the current audit procedures and will begin to realize the extra benefit provided by the disruptive technology. Auditors would then advocate modification to the auditing standards to support adoption of the disruptive technology. Lastly, changes of the business environment could also facilitate modifications of regulation to adopt methodology level disruptive innovations. Emerging technologies adopted by companies such as Big Data can bring significant challenges to the nature of both accounting and auditing (Vasarhelyi et al. 2015). When the enterprise systems continue to grow in size and complexity and companies are recording numerous transactions every day, audit evidence obtained through traditional audit procedures may fail to meet the sufficient and relevant requirement. In this situation, regulators will have the pressure to modify regulations to accept a methodology level disruption that can impact every aspect of audit procedures. Once a disruptive innovation is accepted and adopted in audit, any future improvement will become sustaining innovations, and the technology or methodology will develop inside the audit value network. Similar to the characteristics of disruptive technologies proposed by Christensen (1997), the specific provider of the technology and the exact time of disruption of a disruptive innovation in auditing is virtually unpredictable.

2.4.3 Understanding the Adoption of Continuous Auditing

The proposed framework can be used to understand and analyze the technology adoption process in auditing, especially for disruptive innovations. For example, continuous auditing is considered as a disruptive innovation at methodology level because, instead of examining the actual records, auditing with continuous auditing requires auditors to examine the exceptions (Vasarhelyi et al. 2004). Since the proposing of continuous auditing by Vasarhelyi and Halper (1991), researchers have been constantly developing the theory and arguing the advantages of implementing continuous auditing in external auditing (Brown et al. 2007; Vasarhelyi et al. 2004; Alles et al. 2002; Kogan et al. 1999; CICA/AICPA 1999; Chan and Vasarhelyi 2011). However, despite the fact that using continuous auditing provides timelier, more relevant, and more reliable audit information, a prevalent adoption by external auditors still cannot be seen. Instead, internal auditors are demonstrating much higher enthusiasm in adopting continuous auditing. Case studies and surveys on continuous auditing document a large number of applications associated with internal auditors (Alles et al. 2006; Alles et al. 2008; Vasarhelyi et al. 2012).

In addition to analyzing with technology adoption models, the proposed framework can be utilized to provide one possible reason for the lagged adoption of continuous auditing in external audit. As a disruptive innovation, continuous auditing generates audit evidence from investigating exceptions, which is not fully accepted by the auditing standards and auditors. Consequently, continuous auditing cannot be directly implemented in external audit processes when first proposed. As it constantly being improved by researchers, consultants, and internal auditors, continuous auditing could pressure the audit regulation to change by several ways. Firstly, the widespread adoption of continuous auditing by companies are forcing auditors to obtain more understanding of the methodology, and regulators have also published materials to discuss continuous auditing (PCAOB 2017; Teeter and Vasarhelyi 2015). Secondly, auditors are becoming increasingly aware of the benefits of continuous auditing, and related discussions can be found on the websites of all of the big 4 auditing firms[1]. Lastly, researchers believe that continuous auditing can be an effective solution for auditors to cope with the business environment with an increasing amount of data and information (Vasarhelyi et al. 2015). As companies are entering the Big Data era, regulators may eventually modify the audit process to be based on continuous auditing. Once continuous auditing is fully accepted and adopted in external auditing, it will change the fundamentals of almost every audit procedure. Subsequently, any further improvement on continuous auditing will become sustaining innovation, which is implemented and improved inside the audit value network.

2.5 CONCLUSIONS

Technologies are evolving at an unprecedented pace and have significantly impacted auditors over the last few decades. While researchers have been focusing on

[1] Discussions of continuous auditing by big 4 can be found at:
https://home.kpmg/xx/en/home/services/advisory/risk-consulting/internal-audit-risk/continuous-auditing-and-monitoring.html
https://www2.deloitte.com/content/dam/Deloitte/us/Documents/audit/us-aers-continuous-monitoring-and-continuous-auditing-whitepaper-102910.pdf
https://www.ey.com/Publication/vwLUAssets/EY-advancing-analytics-and-automation-within-internal-audit/$FILE/EY-advancing-analytics-and-automation-within-internal-audit.pdf
https://www.pwc.com/vn/en/services/consulting/continuous-audit-monitoring.html

applying technology adoption models to analyze auditors' adoption of emerging technologies, this essay provides an alternative view from the disruptive innovation aspect. This chapter attempts to expand the TPR theory proposed by Issa et al. (2016) through providing the definitions of sustaining and disruptive innovations in audit, classifying several emerging disruptive technologies, and proposing a framework to illustrate the distinct adoption process of sustaining and disruptive technologies by auditors.

There are several limitations of this study. To begin with, the classification of sustaining and disruptive technologies does not contain any transformation stage. Disruption can be a process rather than a single moment (Christensen 1997). Thus, there is a transforming stage where a disruptive innovation is in the adopting process by the auditors. In addition, only a limited number of emerging disruptive technologies are classified in this essay. Future research can focus on improving the definition of sustaining and disruptive technology in auditing and providing more detailed classification on more emerging technologies. Furthermore, this study proposes the disruptive innovations acceptance framework solely based on theories and conclusions from prior literature. Future research with a series of behavioral experiments or surveys is needed to test the proposed framework and compare auditors' attitudes towards sustaining technologies and disruptive technologies.

CHAPTER 3: CONTRACT ANALYTICS IN AUDITING

3.1 INTRODUCTION

Auditors use contracts extensively for risk assessment, analytical procedures, and substantive tests (PCAOB 2010b, 2010a, 2010e). However, examining contracts for audit-relevant information can be difficult because of the legal expertise required to understand the content and the labor needed to identify and extract useful audit information. Consequently, auditors usually focus on significant or material contracts (e.g., CEO-compensation contracts) and utilize sampling techniques to examine large numbers of contracts associated with low perceived risk (AICPA 2008). With the development of linguistic analysis techniques stemming from natural language processing (NLP) and text mining, computer software and programming tools can now be used to assist auditors in effectively and efficiently analyzing whole populations of contracts. The purpose of this paper is to propose an automated contract analysis framework that incorporates textual analysis to help auditors conduct effective and efficient audit analyses on full populations of contracts that have low perceived risks.

Contracts are important sources of information throughout the audit process. During the audit-planning phase, auditors evaluate contracts on matters related to "knowledge of the company's internal control over financial reporting… matters relating to the company's business, including its organization… and capital structures… [and] the type and extent of available evidence related to the effectiveness of the company's internal control…" (PCAOB 2010a). In addition, contracts can be used as relevant and reliable audit evidence when testing management assertions on existence, valuation, and rights and obligations (PCAOB 2010e). For example, by examining sales contracts that contain price, quantity, discount rate, and payment due date information, auditors can determine whether related sales revenue is properly valued. Also, reviews of long-term bond contracts for information, such as interest rates or bond maturity dates, provide auditors with evidence of the existence and valuation of companies' long-term liabilities.

The latest Accounting Standards Codification (ASC) section 606 (FASB 2016), *Revenue Contracts with Customers,* lays out a five-step process for companies to recognize revenue related to customer contracts: (1) identify the contract(s) with a customer; (2) identify the performance obligations in the contract; (3) determine the transaction price; (4) allocate the transaction price to the performance obligations in the contract; and (5) recognize revenue when the entity satisfies a performance obligation. ASC 606 shifts the current industry-specific revenue recognition principle to the 5-step process based on the specific provisions in each contract (Dyson 2015). Effective December 15, 2017 for public entities and December 15, 2018 for nonpublic entities, this standard places an additional burden of contract examination on both external and internal auditors.

Despite the benefits and the necessity of using contracts to generate solid audit evidence, auditors typically focus on contracts that can significantly impact a firm's financial statement. For those contracts associated with low perceived risks, auditors generally use sampling methods to generate audit evidence. However, samples are not always guaranteed to represent the full population accurately, and individual contracts with low risk may aggregate into a significant amount of risk (Teitlebaum and Robinson 1975).

While some prior literature has examined improving methodologies on audit sampling (Dowling and Leech 2007; Messier Jr et al. 2001), the notion of auditing the entire population of textual documents, such as contracts, has not yet drawn the attention of researchers.

The digitization of contracts and the development of text analytics have opened up the possibility of auditing populations of contractual documents. For instance, Optical character recognition (OCR) allows the extraction of textual content from contracts that are scanned and stored as images in portable document format (PDF) files (Mori et al. 1999). NLP techniques can be implemented on plain text extracted from PDFs for tasks such as parsing and summarization (Dhillon and Modha 2001), text categorization (Namburu et al. 2005), and information extraction (Kanya and Geetha 2007). In addition, prior literature argues that the results of NLP can be utilized by auditors to provide a valuable complement to traditional audit evidence (Yoon et al. 2015). To study practical applications, accounting researchers have used NLP to identify disgruntled employees, flag questionable financial statements, and assess fraud risk (Cecchini et al. 2010a; Goel et al. 2010; Goode and Lacey 2011; Holton 2009; Humpherys et al. 2011). Technological Process Reframing (TPR) theory (Issa et al. 2016) states that with the appearance of disruptive technologies[1] (e.g., NLP and linguistic analysis technology), professionals should reconsider methods and processes adopted in their area. In line with TPR, rapidly

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[1]Disruptive technology, compared to sustaining innovations, is the technology that brings changes that topple the industry's leaders (Christensen 1997). The core of disruptive technology is that it changes the bases of competition by changing the performance metrics along witch firms compete (Danneels 2004).

developing text-analysis technologies should make the auditing realm reconsider audit procedures and evidence related to contract analytics.

In this paper, we propose the Contract Analytics Framework (CAF) which contains high level steps, or functions for auditing whole populations of contracts. The CAF framework consists of six functional areas: (1) *Document Management* deals with importing and managing contracts from various sources; (2) *Content Identification* handles the identification and extraction of audit-related information from contracts including text, numerical data, and tables; (3) *Cutoff Testing* refers to tests that investigate the log information on contracts including temporal information; (4) *Record Confirmation* tests seek to validate and reconcile existing contract data sources (such as an ERP database, or a third party resource) with data extracted directly and automatically from contracts; (5) *Term Verification* tests focus on detecting changes between contract versions, and between a contract in its original template; and (6) *Additional Audit Tasks* lists audit tasks that are supported, or informed by data generated from CAF functions. To add support to these functions, we examine the current auditing standards in the audit stages of risk assessment, substantive tests, and review, and we identify audit procedures related to contracts that can be improved or automated utilizing the CAF framework.

To provide a use case for the CAF framework, we implement it on a small set of reinsurance contracts to assess the feasibility of generating audit evidence from the entire population of contracts. These contracts are similar contracts generated by entering customized information into the same template. The CAF implementation begins with a document management function that imports contracts using optical character recognition

(OCR) and then compares them using cosine similarity scores. Audit related variables are then identified and extracted with regular expressions in the content identification function. The extracted variables and terms are subsequently investigated through the cutoff testing, record confirmation, and term verification functions. The results suggest that the proposed CAF framework can assist auditors in efficiently and effectively examining the full population of contracts and performing related audit tasks.

This study contributes to audit research and practice in several ways. First, it demonstrates the feasibility, through the proposed CAF framework, of incorporating NLP and text mining techniques into contract audit procedures to provide auditors with additional data that can be used to assess audit risk and generate audit evidence. CAF implementations potentially free auditors from repetitive contract examinations, leaving them with more time to handle higher level data. In addition, we map the CAF framework to current auditing standards and preview how the new processes can improve compliance with those standards and increase the reliability of the analyses.

The rest of the paper is organized as follows: Section 2 contains a brief literature review on relevant natural language processing techniques used in accounting research and contracts in auditing. Section 3 proposes the CAF framework and discusses its application in terms of auditing standards. Section 4 includes the results of our implementation of the proposed framework on sample reinsurance contracts. Section 5 concludes the paper.

3.2 LITERATURE REVIEW

NLP and text mining techniques underpin the automated contract analysis process, and in accounting, these techniques have attracted the attention of academics and practitioners for their ability to extract useful information from unstructured text. Keyword extraction from news articles (Lee and Kim 2008), information extraction (Kanya and Geetha 2007), text and abstract summarization (Gupta and Lehal 2010), and text categorization using machine learning (Namburu et al. 2005) are just a few areas covered by text mining that have spurred text analytics in accounting research. Using these techniques, accounting researchers have shown that auditors can use linguistic analyses to flag questionable financial disclosures and assess fraud risk (Humpherys et al. 2011; Goode and Lacey 2011; Goel et al. 2010). Cecchini et al. (2010b) utilized automatic text analysis on Management Discussion and Analysis Sections to aid in identifying firms that encounter fraud or bankruptcy. Text-analysis techniques allow auditors to parse and summarize documents automatically (Dhillon and Modha 2001). Researchers have suggested that in the future text mining will be utilized by auditors to provide valuable complements to traditional audit evidence (Yoon et al. 2015). Moreover, textual data analyses may lead to improvements in management-control systems, budgeting processes, accounting-data quality, and the refinement of accounting standards in financial reporting (Warren Jr et al. 2015). This paper extends the application of accounting text-mining research to contract analyses.

Audits typically emphasize the evaluation of significant contracts. A contract is considered significant if it is material to the client's financial position, or if it provides incentives to management. AS No. 12 requires auditors to obtain understanding of executive-compensation contracts when identifying and assessing the risk of material misstatements (PCAOB 2010c) because such contracts provide management with incentives to successfully operate a business entity (Holthausen et al. 1995). Significant contracts are customized by a firm's legal department or outside lawyers to achieve certain specific objectives. On the other hand, insignificant contracts are immaterial, and individually they pose little risk to the accuracy of financial statements. Low-risk contracts are often created by entering customized information into standard contract templates. For instance, when generating an insurance contract, the company enters data, such as coverage amounts, premium amounts, and effective dates, into a template that contains the insurance policies and clauses. In this way, insurance companies can quickly generate insurance contracts for their clients.

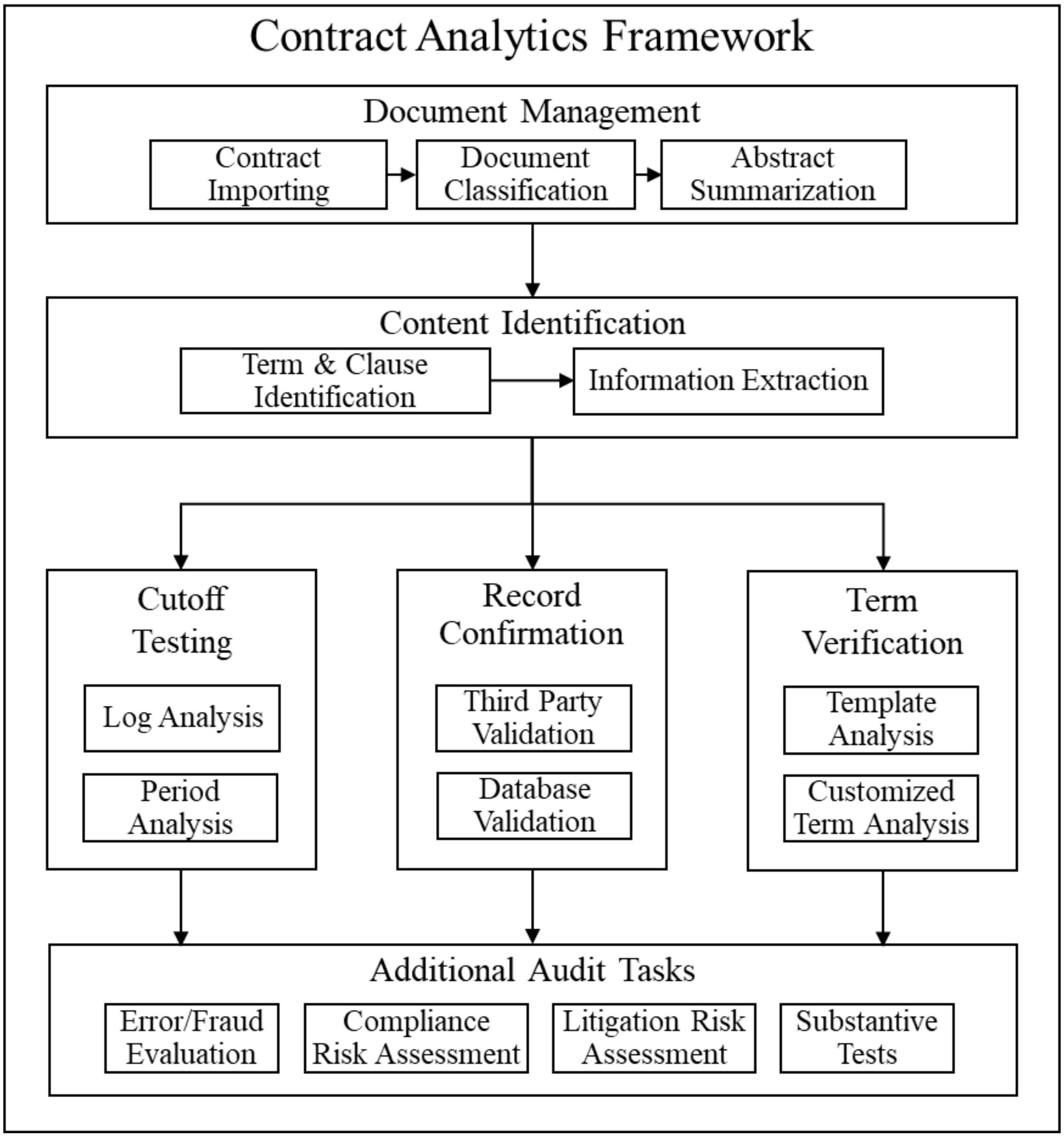
Immaterial template-based contracts, referred to as similar contracts in this paper, are used pervasively across business functions within a company to formalize B2B, B2C, and B2G relationships and transactions. The content of similar contracts consists of a template and variables, customized information entered into the contract template, though the text of the template may be modified as well. Audit-related information is primarily embedded in the variables, as they contain specific amounts agreed upon in the terms of the contracts. Variable data are valuable to auditing, as auditors can use data-analytic tools to analyze data to identify potential risks and fraud (Appelbaum et al. 2016). Conversely, textual content in the template is considered less important insofar as it is composed of boilerplate language. However, alterations, additions, or deletions from the template are potentially of great interest.

Currently, there are two obvious approaches to auditing similar contracts. The first is to audit the client's database, if it exists, of customized variables from similar contracts. Because of the standard process of creating similar contracts, many companies keep digital records of the customized provisions for each contract. Thus, it is feasible for auditors to rely on the client's database, with related internal control tests performed, to audit similar contracts. The drawback of this approach is the dependence on effective internal controls to mitigate human errors and faulty judgements. AU 319 (AICPA 2010) observes that "internal control, no matter how well designed and operated, can provide only reasonable assurance of achieving an entity's control objectives," which suggests that auditing similar contracts with client provided databases will have the same limitation. The second approach is to directly examine the original contracts. This approach provides a higher level of assurance as the audit evidence is obtained from the original documents (PCAOB 2010e). However, the potential high volume of similar contracts and limited auditing resources can force auditors to analyze a relatively small sample of the population, and it may not represent the full population accurately (AICPA 2008). Moreover, risks may only exist and be detectable in aggregate (Teitlebaum and Robinson 1975), rendering sampling ineffectual, obscuring true risks. To facilitate a level of assurance associated with auditing the whole population of similar contracts, we propose the Contract Analytics Framework.

3.3 CONTRACT ANALYTICS FRAMEWORK

While past studies have examined the feasibility of implementing text-mining techniques in auditing (Goel et al. 2010; Goode and Lacey 2011; Humpherys et al. 2011; Yoon et al. 2015), none have explored text mining in the context of auditing contracts. This paper proposes the Contract Analytics Framework (CAF) to provide automation guidance for enhanced audit procedures in contract analyses. Specifically, this framework focuses on supporting the audit of high-volume similar contracts associated with low perceived risk. In contrast to sampling, CAF aims at obtaining audit evidence from the entire population of similar contracts. The framework consists of six main functions: document management, content identification, record confirmation, term verification, cutoff testing, and audit tasks. Figure 3 depicts the CAF framework with its six functional areas their dependencies.

Figure 3: The Contract Analytics Framework



3.3.1 Document Management

The initial CAF functional area, Document Management, handles importing, classifying, and summarizing contract files. The function begins by importing contract documents from different sources, such as enterprise resource planning (ERP) systems, local or online file systems, or physical copies. One prerequisite for applying NLP techniques to text is that the text must be machine readable, thus optical character recognition (OCR) is used to convert scanned images into machine readable text (Mori et al. 1999).

Once the import processes are complete, the next step is to classify the contracts so that auditors can identify and locate contracts related to specific audit tasks, and identify groups of similar, template-based contracts. Similar contracts can be identified by comparing counts, or sequences of common words between documents. Another approach is to identify distinguishing keywords and phrases, and use them to classify contracts. Topics and keywords with high distinguishing power can be obtained using NLP techniques such as keyword extraction and topic generation (Blei et al. 2003; Lee and Kim 2008; McCallum and Nigam 1998).

The third sub-function, abstract summarization, automatically generates a short summary for each contract using text summarization techniques (Gupta and Lehal 2010). Contracts can be numerous, lengthy and complex. Automated abstract generation can be an important tool for assisting auditors in identifying contracts of interest for specific audit tasks.

3.3.2 Content Identification

This functional area refers to the tasks associated with identifying and extracting audit-related information from the textual content of contracts. It begins with identifying terms and clauses related to specific audit tasks, and then extracting and storing relevant content based on those terms and clauses for further testing. For example, when auditors assess internal controls over recording revenue from contracts, terms related to this task are used to identify and extract pertinent information (e.g., price, quantity, date, etc.). One method for identifying relevant terms and any associated data is to manually identify the terms and then codify patterns representing them into regular expressions. A regular expression is a sequence of characters that describes the pattern of a set of strings (Mitkov, 2005). For example, if “Price: ?\$[\d,\.]+” is used as the regular expression search pattern, it will identify any text beginning with the word “Price”, followed by a colon and an optional space. Next, this pattern attempts to match a dollar sign and any combination of digits, commas, and decimal points. For every audit-related variable of interest identified by auditors, a regular expression pattern that matches a variable and accompanying data can be created. These patterns can then be used to search for the same variables in all other similar contracts that are created from the same template. Since similar contracts are generated by filling customized variables to a predefined template, the pattern for matching variables should be consistent across similar contracts. Another term and clause identification technique is to tag terms or clauses using machine-learning systems (Lee and Kim 2008) such as artificial neural networks, support vector machines and naïve Bayesian algorithms (Koskivaara 2004; Li 2010; Perols 2011). These systems learn from training samples consisting of terms and clauses manually tagged and categorized by auditors or experts. Once the systems are trained on the manually tagged information, they can be used to automatically categorize additional terms and clauses for review by auditors. In general, the more training data that is available, the more accurate the classification system. After terms and clauses are identified, they can be automatically extracted for analysis by audit data analytics tools (Vasarhelyi et al. 2015). The Content Identification function is fundamental within the CAF because most of the other functions rely on its output.

3.3.3 Cutoff Testing

The cutoff testing functions are analytical tests that investigate the date and log information of contracts. The date information comprises values in the contract that can include coverage period, effective date, and payment due date. The log information refers to the timestamps of contract events including contract creation, approval, modification, and cancellation. Both of the cutoff testing functions assist auditors in determining which contracts are relevant to the current audit work. For example, auditors can use the log information to determine which sales contracts should be included in the revenue account at year end. During the auditing period, auditors should monitor logs for new or modified contractual agreements. When changes occur and are detected, they can be flagged for inclusion and/or additional analysis.

3.3.4 Record Confirmation

The record confirmation functions of CAF focus on verifying the values extracted from the content identification functions through confirmation and reconciliation. The third-party confirmation subfunction deals with confirming the numbers and terms of contracts with the other parties to the contracts. If necessary, the party names can be identified automatically from the contract text (Rau 1991). Auditors select values and terms from contracts and request confirmation from third parties to verify the existence and accuracy of the information. Robotic automation process (RPA) technology, which refers to the automation of rules-based business process, can be applied in this function to automatically send confirmation request to the third parties and collect the results (Aguirre and Rodriguez 2017).

The database validation sub-function assists auditors in reconciling the numbers and values extracted from contracts to the records stored in their clients' own databases. This function takes as input information (e.g., policy numbers, invoice numbers, transaction IDs, etc.) which has been extracted in the content identification function and matches that information to the related contract data in the client's own database. With automation, this function also allows auditors to reconcile values found in an entire population of contracts, rather than a small number of samples.

3.3.5 Term Verification

The purpose of the Term Verification functional area is to identify anomalies or differences in the terms and clauses used in the contracts. Contracts with lower perceived risks are typically created from a template (e.g., insurance contract) with some customized content. The template analysis subfunction detects alterations in the text of contracts that were formed from templates. Alterations may or may not be legitimate. To detect deviations, straightforward word-by-word comparisons may be sufficient. In cases where an OCR conversion process in the document management function creates noise, word-by-word comparison may be inefficient. Thus, textual similarity measures, such as cosine similarity, and Jaccard similarity may be used to detect anomalies (Gomaa and Fahmy 2013; Pang-Ning et al. 2006).

When contracts contain customized clauses, uncertainty arises in the audit because of additional potential litigation and compliance risks. The customized term analysis sub-function targets the identification of terms or clauses that are unique in customized contracts for further investigation by auditors and specialists. Corpus-based similarity measurements such as latent semantic analysis can be used for such comparisons (Tom et al. 2010).

3.3.6 Additional Audit Tasks

The additional audit tasks in the CAF include evaluations of errors and fraud, assessments of compliance risk and litigation risk, and substantive tests. These tasks can be performed with the resulting data and outcomes from the preceding functional areas. For example, the error and fraud risk can be assessed through the results from the third-party confirmation and database validation. Transactions without supporting contracts, mismatched numbers of contracts with database records, or all otherwise unconfirmed contract data are all areas of potential errors and frauds. A typical terms and phrases detected through term verification functions also signal red flag events. Following the concepts of “exceptional exceptions” developed by Issa (2013), contracts can be listed in the order of potential adverse impacts on financial statements (i.e., the value involved and the likelihood of error or fraud). This list can guide the allocation of working resource and perform risk assessment.

The compliance risk assessment subfunction extracts content from contracts related to regulation compliance. The identification of compliance-related text can be accomplished by searching for explicit statements on compliance issues. For example, the department of banking and insurance in New Jersey imposes a 10-day “free look” provision on life insurance policies, which requires all life insurance contracts to include verbiage that allows customers to exit the insurance policy with refund within a minimum 10-day period (Goldman 2009). The compliance of this regulation can be evaluated by examining the refund provision identified through the Term & Clause Identification subfunction. Auditors can use the extracted content to verify (1) the existence of refund provisions and (2) verify that the grace period is greater than 10 days. Litigation-risk analysis is another complex area that requires legal knowledge. CAF proposes that information from the previous functional areas can inform the calculation of litigation risk, especially when they reveal an inordinate amount of exceptions or deficiencies. Lastly, auditors can use results from cutoff testing, record confirmation, and term verification for substantive tests.

3.3.6 Applying CAF in Current Auditing Standards

Table 4 presents CAF within the typical stages of the audit. Importantly, this table identifies the auditing standards that call for contract analysis directly and indirectly, as well as related automated contract-analysis techniques. Audit procedures are classified into six stages: engagement, planning/risk assessment, compliance and substantive testing, review, reporting, and continuous activities (Appelbaum et al. 2018). Based on current auditing standards, we determined that contract-related audit work is mostly performed within three stages: planning/risk assessment, compliance and substantive testing, and review. Below, we briefly discuss how CAF can be implemented in these three stages.

Table 4: Application of CAF Framework to Current Auditing Standards

	Current Contract Examination by Auditors	CAF Improvement and Automation
Planning/Risk Assessment	Comparing supporting documents (e.g. contracts) to accounting records for the evaluation of internal control (AS No. 5)	Automatic matching numbers in contract with accounting records
	Examine the exposure to losses based on contracts to decide whether the account is significant (AS No. 5)	Identify potential loss related content
	Change in contracts after tests of controls is evaluated to determine whether the effectiveness of company's internal control is affected (AS No. 5)	Log information of new or renegotiated contracts are maintained for examination
	The materiality level can be affected by significant new contracts after initially established (AS No. 11)	Continuous monitoring materiality level relevant terms and clauses from new or renegotiated contracts
	The employment and compensation contracts of executive officers are examined to assist identifying risk of material misstatement (AS No. 12)	Extract content from compensation contracts and present compensation structure for risk analysis
Compliance & Substantive Test	Documentation of auditing procedures includes the inspection of significant contracts or agreements (AS No. 3)	Automatic identify contract with its related audit task and provide key describing characteristics
	Contracts and other agreements are examined to identify related parties (AS No. 18)	Information of related parties in contracts are extracted by ACAAS for further investigation
	Confirming the existence and terms of important contracts is used for fraud detection (AU 316)	Significant terms and clauses are extracted for confirmation and other fraud identification analysis
	Auditing derivative instruments, hedging activities, and investments in securities are based on related contract terms (AU 332)	Valuation characteristics of derivatives, hedging, or other investments are extracted from related controls and used as input of valuation models for evaluation
	Reading contracts, loan agreements, leases, and other similar documents concerning litigation, claims, and assessments (AU 337)	Extract important litigation risk related clauses and terms for further investigation by specialist
Review	Qualitative factors of evaluating audit results include examining the company's compliance with contractual agreements and violations of contractual provisions (AS No.14)	Compliance analysis is performed by extract and aggregate information from identified related contracts and present such information to auditors for compliance evaluation

Planning/Risk Assessment

According to Auditing Standard No. 5 (PCAOB 2007), auditors should confirm their understanding of internal controls by performing procedures that include inspecting related documents through the application of controls. For example, to test the effectiveness of internal controls over recording values of sales contracts in the client database, auditors usually use sampling methods to select a sample of contracts for examination. With automated information extraction technology (Kanya and Geetha 2007) proposed by CAF, information from populations of contracts for understanding and testing internal controls can be identified. This information can then be compared to accounting records within the record confirmation function for auditors to understand and test internal control effectiveness.

During the period of internal control testing, one of the challenges facing auditors is that the results of tests on controls remain effective for only a certain period of time. The CAF cutoff testing function provides one mitigating solution that monitors changes in contracts and agreements by recording the timestamps from the creation, modification, and termination of contracts. Auditing Standard No. 11 requires auditors to re-evaluate established materiality levels when certain changes take place, or when the auditors identify additional information (PCAOB 2010b). With log information monitoring suggested by CAF, auditors can closely observe changes made to a client's contracts and adjust materiality levels accordingly.

To obtain information for determining risks of material misstatements, auditors examine the client company's financial relationships and transactions with its executive officers (PCAOB 2010c). Procedures to obtain such understanding include (1) reading employment and compensation contracts between the company and its executive officers, and (2) reading proxy statements and other relevant company filings (PCAOB 2010c). To supplement or even supplant the manually reading and identification of relevant information, the content-extraction function could automate the process.

Compliance and Substantive Testing

Auditing Standard No. 3 specifies that documentation of auditing procedures related to the inspection of significant contracts or agreements should include abstracts or copies of the documents (PCAOB 2004). The labor-intensive work involved with contract inspection, summarization, and ultimately determination of relevance requires not only auditing expertise, but also legal knowledge. The CAF document classification and abstract summarization functions suggest that this process can be automated. Based on its tagged key words, each contract can be categorized and labeled as relevant to certain specific audit tasks, and subsequently an abstract that summarizes the contract can be generated.

During the compliance and substantive testing phase, investigating relationships or transactions with related parties is a principal task for auditors (PCAOB 2014). When identifying related parties, auditors should examine information from contracts and other agreements with management. Contracts and other agreements representing significant or unusual transactions, or significant contracts renegotiated by the company during the period under audit, merit increased scrutiny (PCAOB 2014). Instead of manually reviewing and identifying potential related party transactions from contracts, the content identification function of CAF provides auditors with automatically extracted information about potential related parties and transactions (e.g., name of related party, amount, transaction date) for further investigation.

Fraud detection is another major audit task to perform during audit field work. AU Section 316 states that, when auditing revenue recognition, auditors should confirm with customers relevant contract terms including acceptance criteria, delivery and payment terms, the right to return the product, and cancellation provisions. The appropriate accounting is often influenced by these terms of agreement (AICPA 2002). The content identification function can be used to identify and extract critical terms, the third-party confirmation function can confirm the existence and accuracy of the terms, and the error/fraud risk evaluation task returns a measure of those potential risks.

Auditors also examine contracts to determine fair-value measurement and accounting estimates (AICPA 2003a, 2003b). Obtaining fair-value-measurement-related audit evidence from contracts requires both manual effort to identify and review related contracts and specific legal knowledge to understand and recognize fair-value-relevant information from contracts. Using text categorization and information extraction functions, algorithms can be trained to identify fair-value information from contracts. The gathered valuation-relevant terms and values provide auditors with critical information about a client firm's fair-value measurements and the accounting-estimation method. This information can be further used by inputting it into pre-built valuation models to determine the fair value of financial derivatives. The same techniques can be applied to identify information related to accounting estimates (AICPA 2003b).

The litigation risk for a client is usually assessed by querying the client's lawyers (AICPA 1976). Other inquiry processes include, but are not limited to, reading contracts, loan agreements, or leases; obtaining information concerning guarantees from bank-confirmation forms; and inspecting other documents for possible guarantees by the client (AICPA 1976). To facilitate these inquiries, CAF functions could be applied to efficiently and effectively identify contracts that carry potential litigation risks. The contract terms and phrases that denote increased risk can be calibrated firm by firm, and the results can inform the audit teams' decisions regarding follow-up interviews and investigations.

Review

During the review stage, auditors should consider both qualitative and quantitative factors to evaluate audit results (PCAOB 2010d). For qualitative factors, auditors should examine the client's compliance with contractual agreements and potential violations of contractual provisions. To this end, CAF functions provide auditors with extracted and aggregated audit-related information from similar contracts for compliance evaluation.

3.4 CAF IMPLEMENTATION

The CAF framework is general and can be implemented according to the needs and circumstances of an audit team. To demonstrate the efficacy of the CAF framework, we provide a relatively narrow implementation. We received a sample of 11 reinsurance contracts from a client of one of the Big Four auditing firms. Ten reinsurance contracts are similar contracts created from the same template and they are more than 99% similar. Each contract has about 29,530 words and they include three subcontracts and ten endorsements. In order to test whether CAF can distinguish between contracts created from a different template, another reinsurance agreement based on a different template from the same client is included in the sample as contract No.11. Since we did not receive the templates for the contracts, and to facilitate the implementation of the CAF functions, we treat contract No.1as the original template. In addition, we intentionally embedded two changes in contract No.2 by moving one paragraph from page 15 to page 3. The page number is determined by the page numbers printed in the bottom right of each page in the PDF file. Thus, adding or subtracting content will not result in a corresponding change of page number.

To begin our exercise, the document management function imports the scanned contracts through an OCR process. The contracts are then grouped based on the template. Subsequently, in the content identification function, audit-related variables are identified and extracted from the contracts using regular expressions. Next, the extracted information is utilized in the record confirmation and cutoff testing functions. Alterations and modifications from the template are also detected with the term verification function by comparing the contracts to the template page by page. Lastly, the results of the use case are discussed in terms of the additional audit task functions and how they help inform auditors' judgments.

3.4.1 Document Management

The objective of the document management function is to preprocess and prepare the contracts for the subsequent steps. In this case study we compare and evaluate contracts based on one template. However, in practice, it is common for a client firm to have multiple templates from which multiple types of contracts are generated. Auditors can adapt this process to accommodate different templates.

Optical Character Recognition (OCR)

Physical signed documents are usually digitized using digital scanners, and the output is often a PDF file that contains images. Reading text from images is difficult for computers because the text is represented as pixels (Jensen and Lulla 1987). The OCR method used in this case study is Google's Tesseract OCR engine (Smith 2007), but the tool, as is typical with OCR software, introduces inaccuracies into data. Often, this is due to a document being scanned at an angle, or artifacts associated with the original printed paper. In our case, when we performed OCR on the sample contracts, some errors occurred during the conversion process because the PDF documents were stored as low-quality, skewed images. Thus, some words and letters were not correctly recognized and digitized. These errors are kept and treated as noise to determine whether the proposed process is noise-resistant.

Similarity between Contracts and the Original Template

Once the OCR process is performed, and the textual content is extracted, the next step is to group contracts generated from the same template. To identify whether the sample contracts are created from the same original template the similarity score between each sample contract and the original template is calculated. We use cosine similarity based on term frequency-inverse document frequency (TF-IDF) (Pang-Ning et al. 2006) to test similarity between sample contracts and the original template.

Cosine similarity measures the similarity between documents by transforming each document into a vector in high dimensional space and measuring the angle between pairs of vectors. To make this vector more meaningful, TF-IDF is used to weight the importance of each word within a document (Salton and Yang 1973; Tata and Patel 2007). The cosine similarity between two documents is then measured by calculating the cosine value of the angle between the two corresponding vectors (Huang 2008). The larger the cosine similarity score is, the higher similarity level between the two documents. High similarity scores are expected among similar contracts created from the same template. A relatively low score may indicate either that the contract is created from a different template, or the contract has been significantly modified. Additional inquires are needed to determine the causes of unusual similarity scores. The standard steps of text retrieval (including tokenization and stemming), described by Baeza-Yates and Ribeiro-Neto (1999), are used to pre-process the contract text before calculating the similarity score.

The cosine similarity scores between each sample contract and the original template, contract No.1, are shown in Table 5. For contracts 2 thru 10, the similarity scores are above 99.5%, which suggest that the textual content in these contracts is largely unchanged from the template. The similarity score for sample No. 11 is 32.570%. This result indicates that No. 11 was customized, modified, or even more likely, not created from the same template as the other samples. If the client includes this contract in the same batch as the other contracts, auditors could consider the low similarity as a red-flag event and subject it to manual inspection. When examining a population of contracts, the threshold for detecting outliers may not be as straightforward as our analysis shown in Table 5. In these situations, algorithms such as DBSCAN and hierarchical clustering (Zhao and Karypis 2002) can be applied to identify outliers.

Table 5: Cosine Similarity Scores between Sample Contracts and the Template

Contract No.	1	2	3	4	5	6
Similarity Score	100.000%	99.958%	99.979%	99.983%	99.976%	99.543%
Contract No.	7	8	9	10	11	
Similarity Score	99.681%	99.669%	99.672%	99.659%	32.570%	

3.4.2 Content Identification

In this stage, auditors manually examine the template of the sample contracts and identify variables that contain relevant audit information. Example variables include sales price, discount rate, and payment due date in a sales contract; or premium amount, effective date, and coverage amounts in an insurance contract. Figure 4 shows the first page of contract No.1, which contains several identified variables. In this use case, we use regular expressions to automatically identify and extract variables from reinsurance contracts. The extracted variables, including both numbers and texts, are stored in a comma separated values (CSV) file.

Figure 4: First Page of Contract No.1

DECLARATIONS

LONG TERM CARE PROFESSIONAL LIABILITY AND GENERAL LIABILITY CLAIMS MADE AND REPORTED INSURANCE;

THIS IS A CLAIMS MADE AND REPORTED INSURANCE POLICY PLEASE READ CAREFULLY
These Declarations and the Policy with Endorsements
shall constitute the contract between the "Insureds" and "Insurer".

Policy Number: A4DB12012013

1. **NAMED INSURED:**

2. **PRINCIPAL ADDRESS:**

3. **PERIOD OF INSURANCE:** FROM: 12/1/2013 TO: 12/1/2014 12:01 AM STANDARD TIME AT THE ADDRESS SHOWN IN ITEM 1 ABOVE.

4. **LIMIT OF LIABILITY:**

POLICY AGGREGATE
$100,000

PROFESSIONAL LIABILITY
$100,000 Each Claim
$100,000 Each Location Aggregate

GENERAL LIABILITY
$100,000 Each Claim
$100,000 Each Location Aggregate
$100,000 Products Completed Operations Aggregate
$100,000 Personal and Advertising Injury Limit
$100,000 Damage To Premises Rented to You Limit
Excluded Medical Expense Limit
Excluded Medical Expense Aggregate Limit

5. **Retention:**
Professional Liability
$0 Each Claim
General Liability
$0 Each Claim

Table 6 presents the results of extracting variables from the 10 reinsurance contracts using regular expressions. The "NA" values refer to situations in which the variable is missing, or an OCR error prevented matching. With the prevalence of contract-generating and -managing software, as well as enhanced hardware, the quality of newer contracts stored in the corporate systems has increased dramatically such that textual content can be converted to text with few, if any, errors.

Table 6: Variable Extraction Results

Variables of Contracts																
Contract Number	Policy Number	Period of Insurance		Limit of Liability								Retention		Gross premium USD$	Retroactive date	
					Professional Liability		General Liability									
		From	To	Policy Aggregate	Each claim	Each Location Aggregate	Each claim	Each Location Aggregate	Products Completed Operations Aggregate	Personal and Advertising Injury Limit	Damage To Premises Rented to You Limit	Professional Liability	General Liability		Professiona l Liability	General Liability
1	A4DB12012013	12/1/2013	12/1/2014	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	NA	11/1/2000	11/2/2000
2	M0DB12012013	12/1/2013	12/1/2014	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$27,675	5/1/2004	5/1/2004
3	A11DB12012013	12/1/2013	12/1/2014	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$35,978	11/1/2000	11/1/2000
4	A12DB12012013	12/1/2013	12/1/2014	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$27,675	11/1/2000	11/1/2000
5	A17DB12012013	12/1/2013	12/1/2014	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$27,675	6/1/2001	6/1/2001
6	NA	12/1/2013	12/1/2014	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$26,292	11/112000	11/1/2000
7	NA	12/1/2013	12/1/2014	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$27,214	5/1/2004	5/1/2004
8	NA	NA	NA	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$27,675	11/1/2000	11/1/2000
9	NA	NA	NA	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$27,675	11/1/2000	11/1/2000
10	NA	NA	NA	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$100,000	$0	$0	$27,675	11/1/2000	11/1/2000

3.4.3 Cutoff Testing, Record Confirmation, and Template Analysis

The extracted variables are used in performing the cutoff testing and record confirmation subfunctions. For cutoff testing, the critical variable to examine is “Period of Insurance,” which specifies the effective dates of the contracts. For the first 7 contracts, the period of insurance is from “12/1/2013” to “12/1/2014,” indicating that they should be examined in the same fiscal year audit. For the last 3 contracts with “NA” as a value, and further manual investigation revealed that this value curiously does not exist. Another relevant variable is “Retroactive Date.” Extracted results show that these reinsurance contracts have the same date for “Professional Liability” and “General Liability” and the common date period is from “11/1/2000” to “5/1/2004”. Suspicious contracts can be identified if these two dates are different, or if the retroactive dates are earlier than usual.

The record confirmation function is applied next. Importantly, all the contracts with missing data, such as “Policy Number” and “Gross Premium USD$,” require further inquiry by auditors. This can be accomplished by matching the extracted “Policy Number” to corresponding records in the client database. In a larger sample, audit data analytic tools could be applied to further analyze the data. For example, in this case a visual inspection reveals that “gross premium” of contract No. 3 has an unusually high value compared to the other samples.

3.4.4 Template Analysis

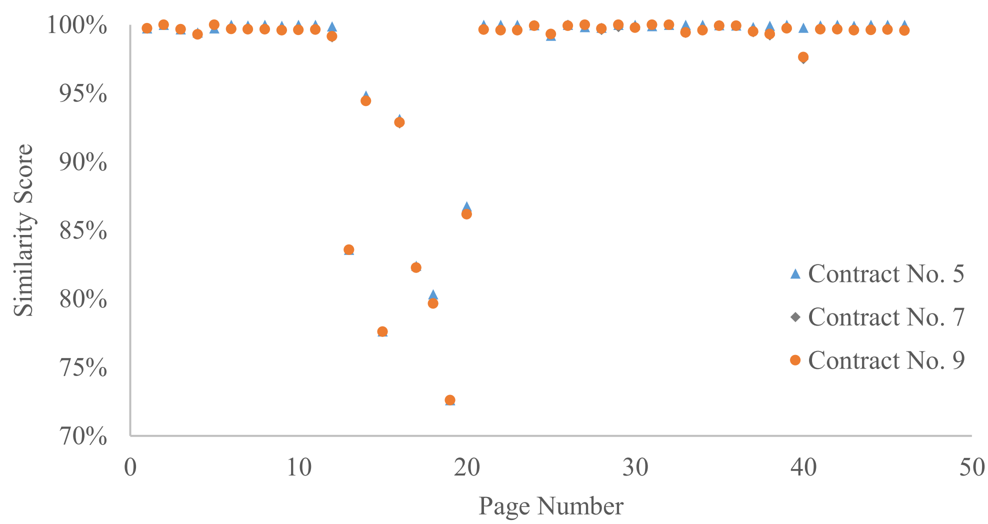
The Template Analysis function detects modifications in contracts from the original template. Examples of anomalies that will be detected include the subtraction or addition of a sentence or paragraph, or alterations of terms and clauses. To accomplish this, we implement a page-by-page comparison. Specifically, we compute the cosine similarity score between each page of each sample and the corresponding page in the original template. If the sample has not been modified, high similarity scores are expected. Subtractions, additions, and alterations on a certain page should lower page-by-page similarity scores.

The results are presented in Figure 5 and Figure 6. Figure 5 contains the page-by-page comparisons of contracts 2, 3, and 10 to the template. The similarity scores are presented on the vertical axis, and the page numbers are presented on the horizontal axis. The similarity scores that are near 100% indicate that these pages are almost identical to the template. Contract No. 3 is a contract with no deviations from the template apart from variable values. In contract No. 2 we moved a paragraph from Page 15 (94.10% similarity) to Page 3 (96.62% similarity), and the changes were detected by the algorithm. Page 40 (97.60% similarity) of contract 10 received an unexpectedly low similarity score. Visual inspection confirmed that a sequence of characters on the template, “CG 04 35 12 07”, was missing from this contract although the purpose of the sequence is unknown.

Figure 5: The Page-by-page Similarity Scores of Contract Nos. 2, 3, and 10

Figure 6 shows the page-by-page similarity scores for sample contracts 5, 7, and 9. A total of eight pages in the three documents have relatively low scores. A manual comparison of PDF files revealed that these three samples contain the same textual content as the template. However, inspecting the digitized text confirmed that the converted OCR process produced errors and was the cause of the deviations. This problem could probably be solved with higher-quality PDFs.

Figure 6: The Page-by-page Similarity Scores of Contract Nos. 5, 7, and 9



3.4.5 Additional Audit Tasks

Results from preceding functions can be compiled to assist auditors performing various audit tasks. Specifically, the full-population based result can be used to detect fraud and error, assess litigation and compliance risks, and serve as substantive tests. When evaluating the possibility of error and fraud, auditors should consider the anomalies detected from cutoff testing (e.g., missing "Period of Insurance"), record confirmation (e.g., missing or unconformable "Gross Premium USD$"), and term verification (e.g., 2 irregular scores from contract No. 2). Analyzing information extracted directly from full populations of source contracts can serve as solid substantive tests and increase the reliability and relevance of audit evidence obtained to test management's assertions of existence, completeness, and valuation (PCAOB 2010e). Although only a limited number of sample contracts were examined in this case, the CAF framework can be implemented to assist auditors at a much larger scale.

3.5 CONCLUSION AND FUTURE WORK

Auditors use contracts as important audit related documents during risk assessments, substantive testing, and audit reviews. However, more emphasis is placed on major, or so-called material contracts, which have a significant and obvious financial impact on the client company. Contracts with low perceived risks usually receive relatively little attention from auditors and are investigated with audit-sampling techniques. Nevertheless, due to the large quantity of such contracts, minor errors or fraud may aggregate and lead to significant risks. Developments in linguistic-analysis techniques allow efficient textual analysis that can be utilized by auditors (Cecchini et al. 2010b; Goel et al. 2010; Goode and Lacey 2011; Warren Jr et al. 2015), allowing for the performance of full population contract audits.

This paper proposes the CAF framework that incorporates NLP and text mining techniques to provide auditors automation suggestions and guidance to investigate populations of contracts with low perceived risks. CAF includes six functional areas that guide auditors through contract-related audit tasks on the entire population of contracts. The framework is implemented on an illustrative sample of reinsurance contracts and the results support the feasibility of extracting audit-related content, detecting value and text-based anomalies, and generating audit evidence.

There are several limitations to the proposed CAF framework. First, current auditing standards require risk-based audit methodologies that do not necessarily encourage full-population audits. Until auditing standards are written with population-level audits in mind, the adoption and application of our proposed framework, or similar ones, may lag. As auditing standards become more data-oriented, processes like the one proposed in this paper may become standardized as innovative analytic techniques continue to emerge. Second, the framework does not handle handwritten content in contracts. Handwritten content, such as signatures and ad-hoc changes, are common in contracts and may contain significant audit related information. Currently, researchers are building machine learning handwriting recognition tools (Keysers et al. 2017) and future work is needed to ensure handwriting related functions such as signature detection and signature verification are integrated into auditing procedures.

There are also limitations to our implementation of the CAF framework. First, we limit our data to one set of similar contracts. The implementation would be more informative if it dealt with customized contracts, or several different sets of similar contracts. The implementation is based on a small sample of 11 contracts, precluding the opportunity to perform population-wide data analytic functions we promote in this paper. In addition, the low quality of the PDFs could impact the results. The lower the image's quality is, the more errors OCR will make when digitizing texts. This could lead auditors to extract erroneous data from the contracts, making functions such as cutoff testing, record confirmation, and term verification unusable. In this situation, auditors may choose to manually correct the OCR errors, to rely on the client's database, or revert to sampling methods. Although our sample size is small, and the PDFs are of variable quality, the implementation helps demonstrates the feasibility of the framework.

Currently, there are various commercial software tools that embed NLP techniques for contract management. These commercial tools can handle tasks such as OCR, contract classification, and the identification and tagging of relevant content. However, they have been developed for and applied to contract analysis from a legal perspective. The CAF framework details the processes for dealing with contract analysis from an audit perspective.

This paper demonstrates how auditing may change due to advances in technology. Technological process reframing theory (Issa et al. 2016) predicts that technology will disrupt areas of endeavor by replacing their current processes and methods with more informative and efficient ones. The digitization of data, improved communication protocols (the Internet), and cheap storage mediums have led to the era of Big Data and ubiquitous data analytics. Automated contract analysis is a natural progression and it represents the reframing, or change in contract analysis methodologies.

CHAPTER 4: IMPACT OF BUSINESS ANALYTICS AND ENTERPRISE SYSTEMS ON MANAGERIAL ACCOUNTING

4.1 INTRODUCTION

Over the years, the role of management accountants has significantly changed. Serving the purpose of assisting and participating in decision making with management, modern management accountants work from four aspects: to participate in strategic cost management for achieving long-term goals; to implement management and operational control for corporate performance measure; to plan for internal cost activity; and to prepare financial statements (Brands 2015). As business competition has increased tangentially with technology development, the scope of managerial accounting has also expanded from historical value reporting to more real time reporting and predictive reporting (Cokins 2013).

While enterprise systems provide improved effectiveness and efficiency of management accountant tasks, studies indicate that management techniques have not changed significantly (Granlund and Malmi 2002; Scapens and Jazayeri 2003). The argument is that management accounting principles and standards used by organizations prior to the implementation of enterprise systems have not changed. To provide more relevant and valuable information to management in this highly technical business environment, management accountants should be further utilizing all of the functions of the enterprise system (e.g. descriptive, predictive, and prescriptive data analytics; Big Data from both internal and external sources; and financial and non-financial information) rather than considering the system merely as a more powerful calculator.

The purpose of this paper is to discuss the potential impact of enterprise systems, Big Data, and data analytics on managerial accounting and to provide a framework that implements business analytics techniques into the enterprise system for measuring company performance using the balanced score card (BSC) framework from a management accounting perspective. While some literature describes the impact of business analytics on management accounting (Nielsen 2015; Silvi et al. 2010), little research discusses using business analytics for measuring a company's performance in an enterprise system environment (Nielsen et al. 2014).

This paper contributes to the literature in several ways. First, this paper discusses the impact of business analytics on managerial accounting from an enterprise system perspective. Although some researchers have proposed a BSC framework for management accountants to apply business analytics (Nielsen 2015; Silvi et al. 2010), few have examined this issue within the enterprise systems context. Second, this study proposes the Managerial Accounting Data Analytics (MADA) framework that incorporates the BSC framework for management accountants to utilize data analytics for corporate performance measurement. Lastly, attributes related to the implementation of a MADA framework (i.e. business intelligence context, data quality and integrity) are discussed to build the connection of the MADA framework and modern business practice.

The paper is organized as follows: The next section discusses the changing role of management accountants and the impact of enterprise systems on managerial accounting.

The development of business analytics and Big Data, as well as their impact on enterprise systems are reviewed next, followed by the development of the proposed Managerial Accounting Data Analytics (MADA) framework. This MADA framework is then applied in the Business Intelligence (BI) environment, followed by a discussion of relevant issues. The paper concludes by briefly expanding on suggestions for future research.

4.2 CHANGING ROLE OF MANAGERIAL ACCOUNTING

4.2.1 Management Accountant's Role

Evolving from its traditional emphasis on financially-oriented decision analysis and budgetary control, modern managerial accounting encompasses a more strategic approach that emphasizes the identification, measurement, and management of the key financial and operational drivers of shareholder value (Ittner and Larcker 2001). The goal of management accounting is to provide managers with operational and financial accounting information. Management accountants serve the role of participating in strategic cost management for achieving long-term goals; implementing management and operational control for corporate performance measurement; planning for internal cost activity; and preparing financial statements (Brands 2015). To support this intended role, the main obligations of management accountants can be classified into (1) preparing financial statements; (2) measuring the company's performance; and (3) providing decision related information (Cokins 2013).

With ERP systems and powerful business analytic tools that provide enterprises the ability to interpret and analyze various types of data (such as internal/external, structured/unstructured and financial/nonfinancial), it is crucial for management accountants to adjust their responsibility to help companies gain competitive advantage (Nielsen 2015). In the preparation of financial statements, management accountants use accumulated historical values to report the financial situation of the company. However, in a business world that requires more timely and relevant information, financial statements usually are not an ideal source of information for decision-making by management as they are backward looking, reporting on past events rather than providing the forward-looking data needed for running the business. Modern management accountants assist management with measuring firm performance from internal data and providing decision related information from both internal and external data. Not only should management accountants provide descriptive reports to answer questions about prior events, they also need to make predictions including consequences for uncertainty and risk in decisions (Nielsen 2015).

To fulfill these challenging tasks that help the business stay competitive, management accountants now can use business analytical tools to conduct prescriptive analysis to support decision makers against the uncertainties. For example, an optimization model could allow accountants in a manufacturing company to choose among different raw material vendors that could reduce cost and boost revenue (Taleizadeh et al. 2015). It is suggested that management accountants should transgress the boundaries of management accounting and interact with non-accountants to solve practical problems (Birnberg 2009). Cokins (2013) highlights seven trends that are occurring in management accounting: (1) expansion from product to channel and customer profitability analysis; (2) management accounting's expanding role with enterprise performance management (EPM); (3) the shift to predictive accounting; (4) business analytics embedded in EPM methods; (5) coexisting and improved management accounting methods; (6) managing information technology and shared services as a business; and (7) the need for better skills and competency with behavioral cost management. In summary, management accounting has broadened its domain from conventional financial reporting to also including performance measurement and strategic decision making. Specifically, management accounting has extended its traditional focus to include identifying the drivers of financial performance, both internal and external to the business. New and revolutionary non-financial metrics and approaches have been added to management accounting functions, with an impact that is still being studied by academics and practitioners (Silvi et al. 2010).

4.2.2 ERP Systems

Enterprise Resource Planning (ERP) systems are organization-wide and integrated information systems that are capable of managing and coordinating all the resources, information, and functions of a business from shared data stores (Kallunki et al. 2011). Since ERP systems can integrate transaction-based corporate information into one central database and allow that information to be retrieved from different organizational divisions (Dechow and Mouritsen 2005), they can improve the capability of management accountants to fulfill the aforementioned roles by providing management with access to relevant and real-time operational data in the support of decision making and management control.

Early research suggests that ERP systems have limited impact on management accounting (Granlund and Malmi 2002). One of the reasons is that the implementation of ERP systems focuses on improving the efficiency of the financial reporting process and not changing the nature of that process, even though change could be obtained through the design and implementation of a system that integrates the operations of the entire organizations (Sangster et al. 2009). That is, management accountants consider the ERP system as a powerful tool for report generation and neglect its potential in process control and corporate performance analysis.

For a successful ERP implementation, Grabski et al. (2009) point out that the nature of management accounting's role should be changed dramatically, whereby the management accountant becomes a business advisor who takes proactive steps to aid executives and decision makers. Specifically, they describe the interactive relationship between ERP systems and management accountants as follows (Grabski et al. 2009):

> "1. When management accountants are involved in an ERP system implementation, there is an increased likelihood of the implementation being a success.
>
> 2. The impact of the ERP system on the role of the management accountant is related to the perceived success of the system implementation, with more successful implementations exhibiting the more dramatic changes to the role.
>
> 3. While all ERP implementations results in changes in the tasks performed by management accountants, a successful ERP implementation results in a significant change in the management accountant's tasks, they become business partners not just data providers.
>
> 4. A successful ERP implementation results in both increases in data quality and quality of decision-making, and in additional time for management accountants to become involved in value-adding tasks rather than mundane data recording and information reporting tasks.
>
> 5. Management accountants in an ERP environment need a strong understanding of the business and the business processes, significant

interpersonal skills, leadership skills, decision-making skills, analytical skills, planning skills and technical skills.

6. The role of management accountants in an ERP environment is more that of a business advisor to top management than that of a traditional management accountant."

Furthermore, Scapens and Jazayeri (2003) propose that with the ability of ERP systems, management accountants have the potential to report more forward-looking (predictive) information and to provide more direct support to business managers with the computerization of many traditional accounting tasks. For management accountants to be able to provide more predictive reports, the data available to support such analyses may need to be more varied and voluminous – that is, big data.

4.3 BIG DATA AND BUSINESS ANALYTICS

Big data and business analytics now influence almost every aspect of major companies' decision making, strategic analysis, and forecasting (Griffin and Wright 2015). On any given day, a business might create, purchase, extract, collect, process, and analyze millions of data elements from external and/or internal sources to maintain competitive advantage. Big data and business analytics are no longer the domain of a few initial innovators and adopters; they are ubiquitous for any business that wants to remain competitive (Davenport 2006). Since management accountants traditionally utilize information generated from accounting records to assist business managers, it is anticipated that the availability and use of big data and analytics by businesses will impact the managerial accounting profession. However, first it is necessary to understand big data and business analytics in the internal business environment and its context.

4.3.1 Impact of Big Data on the Business Enterprise System

Big data could be regarded as data sets so large or unstructured that they cannot be processed and analyzed easily using most database management systems and software programs (Warren Jr et al. 2015). Big data in its entirety can originate from traditional transaction systems as well as from new unstructured sources such as emails, audio files, internet click streams, social media, news media, sensor recordings, videos, and RFID tags (Zhang et al. 2015). Big data has become characterized by four qualities or the four V's: immense Volume, high Velocity, broad Variety, and uncertain Veracity (Laney 2001; IBM 2012).

Historically, business and accounting data reported transactions and other structured data, such as orders, sales, purchase orders, shipments, receivables, personnel information, time sheets, and inventory. This data is predictable, orderly, and familiar to businesses. This type of data stands in contrast to big data. Where the former data was structured in rows and columns, the latter data that is not structured and may seem overwhelming to work with due to the volume, variety and data type. The emergence of big data has changed the management accountant's task. A business utilizing big data would have invested significant resources to collect, process, prepare, and eventually analyze it and consequently expects deeper insights and knowledge as results.

Essential for any type of data, beyond being big or not, is that it be of high quality (Chae et al. 2014). High quality data is complete, precise, valid, accurate, relevant, consistent, and timely (Redman 2008). Research shows that high quality data is an important business resource and asset (Chae and Olson 2013; Redman 1996) and has tremendous impact on an entity's performance (Forslund and Jonsson 2007; Gorla et al. 2010). Poor quality data of any type and from any source can negatively impact the management accountant's work, rendering forecasts to be in error. Valuable analysis and forecasts are a result of the most appropriate analytical approach(es) applied to high quality data. Or, as stated by Davenport et al. (2010): "You can't be analytical without data, and you can't be really good at analytics without really good data."

4.3.2 Classification of Business Analytics

Business analytics is 'the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their operations, and make better, fact-based decisions' (Davenport and Harris 2007). The recently proposed three dimensions of domain, orientation, and techniques (Holsapple et al. 2014) are useful for understanding the scope of business analytics. Domain refers to the context or environment in which the analytics are being applied. Orientation describes the outlook of the analytics – descriptive, predictive, or prescriptive. And finally, techniques refer to the analytical processes of the domain and orientation. The feasibility of the application of any one technique is decided not only by its orientation, but also by the available data.

For this discussion, the domain dimension is business management. Management accountants in this domain are expected to create systems that align with management duties and goals. The three dimensions of orientation (i.e., descriptive, predictive, and prescriptive) should now be clarified to gain an understanding of their potential in the managerial accounting domain. The differing orientations of these dimensions are partly due to the availability of different types of data in conjunction with various techniques and the capabilities of enterprise systems to handle big data.

Descriptive Analytics

Descriptive analytics answers the question as to what happened. It is the most common type of analytics used by businesses (IBM 2013) and is typically characterized by descriptive statistics, Key Performance Indicators (KPIs), dashboards, or other types of visualizations (Dilla et al. 2010). Descriptive analytics summarize what has happened and which also forms the basis of many continuous monitoring alert systems, where transactions are compared to benchmarks and thresholds are established from ratio and trend analysis of historical data.

Predictive Analytics

Predictive Analytics is the next step taken with the knowledge acquisition from descriptive analytics (Bertsimas and Kallus 2014) and answers the question of what could happen (IBM 2013). It is characterized by predictive and probability models, forecasts, statistical analysis and scoring models. Predictive models use historical data accumulated over time to make calculations of probable future events. Most businesses use predominantly descriptive analytics and are just beginning to use predictive analytics (IBM 2013).

Prescriptive Analytics

Prescriptive Analytics (Bertsimas and Kallus 2014; Holsapple et al. 2014; IBM 2013; Ayata 2012) answers the question of what should be done given the descriptive and predictive analytics results. Prescriptive analytics may be described as an optimization approach. Prescriptive analytics go beyond descriptive and predictive by recommending one or more solutions and showing the likely outcome of each.

The techniques for predictive and prescriptive analytics may appear similar, but their orientation and ability to prescribe depends on the type and amount of data available for analysis. The more varied the data types, the more likely the solution may be prescriptive. Prescriptive techniques may utilize quantitative and qualitative data from internal and external sources. The main difference between prescriptive and predictive analytics is not one of required data types, but one of orientation – that is, is this an optimization query or a trend-based analysis? What are the questions critical to management? Analytics based on quantitative financial data alone are utilizing only a fraction of all available data, since most data is qualitative (Basu 2013). Based on business rules, constraints, and thresholds, in a prescriptive orientation, mathematical simulation models or operational optimization models are built that identify uncertainties and offer solutions to mitigate the accompanying risks or adverse forecasts.

More importantly, prescriptive analytics can take in all types of new data to re-prescribe and then refine prescriptions based on a feedback loop. Prescriptive analytics can automatically improve prediction accuracy and best decision choice scenarios. Business analytics undertaken by management accountants where big data is available may result in a prescriptive analytics approach where a set of techniques computationally identifies several alternative actions to be taken by management, given their complex objectives and limitations, with the goal of reducing business risk. For example, external social media could be used to project the optimal marketing budget and reduce the risk of directing resources in the wrong market segment. Social media and other new or refreshed exogenous data could also be used to re-estimate and re-run models, based on changes in the business environment, economic conditions, government policies, and unexpected events.

The techniques of business analytics can be considered as either qualitative or quantitative, or as deterministic or statistical, or based on unstructured, semi-structured, or structured data (Table 7). The most traditionally used accounting techniques are those that are quantitative, statistical, and based on structured data. While in the past most advanced business analytics techniques came from statistical data analysis, more recently research has begun incorporating techniques that originate in machine learning, artificial intelligence (AI), deep learning, text mining, and data mining (Oracle 2015; Schneider et al. 2015; Warren Jr et al. 2015). Some of these techniques do not make any statistical assumptions about underlying data, and consequently generate models that are not statistical in nature. The techniques of business analytics are classified as follows in Table 7.

Table 7: The Orientation and Techniques of Business Analytics in the Managerial Accounting Domain

Orientation	**Techniques**		**Technique Type**			
Descriptive (D) Predictive (PD) Prescriptive (PS)			**Exploratory (E) Confirmatory (C)**	**Structured(S) Semi-Structured (SS) Unstructured(U)**	**Quantitative (QN) Qualitative (QL)**	**Deterministic (D) Statistical (S)**
D	**Basic Accounting Analysis**	Ratio Analysis	C	S	QN	D
D	**Unsupervised**	Clustering Models	E	S	QN	S
D		Text Mining Models	E	SS, U	QL	S
D		Visualizations	E	SS, U	QL, QN	S
D		Process Mining: Process discovery models	E	S, SS	QN	S
PD	**Supervised**	Process Mining: Process Optimizations	C	S, SS	QN	S
PD		Support Vector Machines (SVM)	C	S	QN	S
PD, PS		Artificial Neural Networks (ANN)	C	S	QN	S
PD, PS		Genetic Algorithms	C	S	QN	S
PD, PS		Expert Systems/Decision Aids	C	S, SS,U	QN, QL	S
PD		Bagging and Boosting models	C	S	QN	S
PD		C4.5 statistical classifiers	C	S	QN	S
PD		Bayesian Theory/Bayesian Belief Networks (BBN)	C	S	QN	S
PD		Dempster-Shafer Theory Models	C	S	QN	S
PD		Probability Theory Models	C	S	QN	S
PD. PS	**Regression**	Log Regression	C	S	QN	S
PD, PS		Linear Regression	C	S	QN	S
PD, PS		Time Series Regression	C	S	QN	S
PD, PS		Auto Regressive Integrated Moving Average (ARIMA)	C	S	QN	S

PD, PS		Univariate and Multivariate Regression Analysis	C	S	QN	S
PD	**Other Statistics**	Multi-criteria Decision Aid	C	S	QN	S
PD		Benford's Law	C	S	QN	S
D		Descriptive Statistics	E	S	QN	S
PD		Structural Models	C	S	QN	S
PD		Analytical Hierarchy Processes (AHP)	C	S	QN	S
D		Spearman Rank Correlation Measurements	E	S	QN	S
PD		Hypothesis Evaluations	C	S	QN	S
PD,PS		Monte Carlo Study/Simulation	C	S	QN	S

Table 7 reports the Orientation and Techniques of business analytics in the managerial accounting domain, where:
D, PD, PS = Descriptive, Predictive, Prescriptive
E, C = Exploratory, Confirmatory
S, SS, U = Structured, Semi-Structured, Unstructured
QN, QL = Quantitative, Qualitative
D ,S =Deterministic, Statistical
adapted from Appelbaum et al. (2018)

Visualizations, in the forms of dashboards and menus, are already quite common in business use (Dilla et al. 2010). These are ubiquitous with the Balanced Scorecard (BSC) (Kaplan 2008) method and in most BI applications. Furthermore, business management in general prefers the results of analysis to be presented in an easily understood format (Kohavi et al. 2004; Davenport 2014), so typically reports are in the format of pie charts, heat maps, geo-maps, and other charts to facilitate quick understanding (Davenport 2014). Management generally has little desire to wade through complex analysis and reports. Even though the enterprise system is expected to facilitate complex predictions and optimizations, management accountants are expected to be able to communicate these findings clearly with easily understood visualization tools.

4.3.3 Enterprise Systems with Big Data and Business Analytics

As discussed earlier, enterprise systems applications are software packages that are generally based on relational databases, which impact and facilitate business events such as order capturing, to accounting, and to warehouse management (Edwards 2001). All levels and sources of information are entered in the system once, at the time of occurrence, and the enterprise-wide scope of the system allows this new data to be instantly available anywhere internally. Enterprise systems resulted from the need by business management to plan, manage, and account for resources and activities in a real-time, relevant, and insightful manner (Edwards 2001). Previously disconnected legacy systems have been replaced by, or more commonly connected to, integrated enterprise systems in many businesses to provide improved support for more impactful insights and subsequent decisions and actions. Furthermore, the cloud, big data, business analytics, and a competitive business environment are challenging the functions and scope of enterprise systems and driving businesses to realize new “actionable insights” and better outcomes from these new capacities and capabilities (Oracle 2015).

The integration of these various external big data streams along with the increasing volume of internal data in the enterprise environment could create challenges. It could become unmanageable unless the enterprise system is re-engineered to accommodate the new complexities presented by different data streams and advanced business analytics.

In a big data context, business analytics is faced with several challenges: complex data extracts, data fluctuations, data duplications, data security weaknesses, and the potential for multiple analytical tools and languages (such as SAS, SAP, R, SQL, Python, SPSS and Tableau,). Furthermore, traditional analytical and machine learning methodology may pose problems in a big data enterprise system context. For example, typical data analysis begins by extracting a representative sample or “training set” of the data to a separate “sandbox” environment where tools such as SAS, R, Python, or SPSS may be applied. A descriptive, predictive, or prescriptive model or solution is then developed or built and which is determined to be applicable and beneficial. However, this model and all its associated data preparation and transformation steps will need to be somehow transposed into SQL (most enterprise systems) and recreated for “mass analysis” internal to the system. This conversion can be a time consuming and error prone process.

Enterprise system providers are beginning to offer this functionality so that businesses may take full advantage of the actionable benefits that big data analytics can provide (Oracle 2015). These systems also prepare the data for analysis. Data is cleaned, normalized, and formatted prior to extraction. These enterprise systems allow management accountants to access more information exogenous and endogenous to the firm and provide informed predictions, all while working with big data internally. R and other open source applications such as Python are accessible directly within the enterprise system (Oracle 2015). Accountants can build automated analytical applications within the system once the tasks have been defined (Oracle 2015). With these new capacities of modern enterprise systems, and the possibilities presented by big data and business analytics, management accountants can do more than simply monitoring and tracking key indicators of historical financial reports.

4.4 INTEGRATION OF DATA ANALYTICS IN ERP SYSTEMS FOR MANAGEMENT ACCOUNTING

This section proposes the Managerial Accounting Data Analytics (MADA) framework that integrates data analytics in enterprise systems for management accounting purposes based on the balanced scorecard (BSC) concept.

4.4.1 Balanced Scorecard Theory

BSC was first developed by Kaplan and Norton (1992) to supplement traditional financial measures. The proponents argue that traditional financial measures are lag indicators that report on the outcomes from past actions and that BSC supplements this information with measures on the drivers, the lead indicators, of future financial performance. The BSC framework measures corporate performance from four perspectives: financial (how do we look to shareholders?), customer (how do customers see us?), internal business processes (what must we excel at?), and learning and growth (can we continue to improve and create value?). Specifically, Kaplan and Norton (2001) interpret BSC as a framework for organizing strategic objectives and illustrate four perspectives as follows: "Financial—the strategy for growth, profitability, and risk viewed from the perspective of the shareholder; Customer—the strategy for creating value and differentiation from the perspective of the customer; Internal Business Processes—the strategic priorities for various business processes that create customer and shareholder satisfaction; and Learning and Growth—the priorities to create a climate that supports organizational change, innovation, and growth" (Kaplan and Norton 2001). Empirical studies have found a positive relationship between implementation of BSC and long-term financial performance (Davis and Albright 2004; Yancy 2014).

BSC provides an opportunity to integrate data analytics methods into ERP systems for the purpose of measuring corporate performance. Specifically, various types of data analytics can be supported by data warehouses that combine external big data with the enterprise data that includes such large volume data streams such as RFID feeds. Management accountants then can benefit from data analytics by measuring the corporate performance or providing management with other useful information.

4.4.2 Managerial Accounting Data Analytics (MADA) Framework

Figure 7 exhibits the framework for implementing data analytics in managerial accounting based on balanced scorecard theory. According to Cokins (2013), management accounting can be classified into cost accounting, cost reporting and analysis, and decision support with cost planning. Thus, in this framework, management accounting is classified into cost accounting, performance measurement, and planning and decision making. In cost accounting, management accountants focus on using internal data to generate financial reports of the organization. Performance measurement focuses on the insights, inferences, and analysis of the processes or events that have taken place to measure corporate performance. Data used in performance measurement includes mostly internal data. However, external data, such as industry benchmark information, can be used for performance evaluation. Planning and decision making involves using the result of both cost accounting and performance measurement to provide accurate, timely, and relevant information in combination with other external information to assist management. External data are heavily used in combination with internal data to provide relevant information for decision making.

Data analytics can be implemented to assist management accountants in all three aspects of management accounting. For financial reporting purposes, the most applicable type of data analytics is descriptive analytics which helps to summarize and describe the financial situation of a business. In the field of performance measurement, management accountants can utilize predictive analytics, which can employ machine learning algorithms with inputs from descriptive analytics, to provide prediction of future organization performance. With the results from both cost accounting and performance measurement, prescriptive analytics are incorporated into planning and decision making to provide information regarding the optimized solution for decision makers. Serving as the data source of data analytics, big data is comprised of both internal and external data. Internal data represents data gathered inside the entity (i.e., the company's database). This type of data is generally structured and familiar to management accountants. On the other hand, external data represents data collected from sources outside the company, such as news, social media, or Internet of Things (IoT). Usually, external data are unstructured data that can only provide information after being processed by analytics tools. Data types listed in both internal and external boxes represent only examples, not the inclusive list of the entire internal and external data types.

In this framework, the BSC methodology is implemented under performance measurement and planning and decision making aspects of management accounting for the purpose of incorporating data analytics in the related process. For each perspective of the BSC (financial, customer, internal process, and learning and growth), different types of data analytics are applied to provide a comprehensive measurement of each perspective.

Figure 7: The Managerial Accounting Data Analytics (MADA) Framework

[redacted]

Financial Perspective

The ultimate goal of profit-seeking corporations is to increase shareholder value. Kaplan and Norton (2001) point out that companies increase economic value through revenue growth and productivity. Revenue growth generally includes two components: new initiatives (new markets, new products, and new customers); and increase sales of products or services on existing customers by deepening the relationship with them. The financial perspective of BSC measures the financial situation of a company. Cash flow, sales grow rate, market shares, or return on equity (ROE) are examples of measures that reflect the financial perspective of the company (Kaplan and Norton 1992).

Descriptive data analytics provides management accountants the overall view of the current financial performance of the company. For example, ratio analysis that compares ROE and return on investment (ROI) with historical data gives management accountants the information on the growth of the company. On the other hand, comparing such ratios with industry benchmark data describes whether the company maintains competitive advantage. Interactive visualization tools allow managerial accountants to present financial information much more effectively.

Predictive analytics use accumulated historical data to estimate possible future events. In the financial perspective, predictive analytics are commonly applied for predicting future financial performance. The algorithms for prediction can be classified as either supervised or unsupervised. Examples of supervised algorithms include support vector machines (SVM), artificial neural networks (ANN), genetic algorithms, bagging and boosting models, C4.5 statistical classifiers and Bayesian Belief Networks (BBN)[1]. Such supervised algorithms develop the model based on datasets with output. In contrast, unsupervised algorithms do not require datasets with output. Specifically, they classify or cluster the data into different classes, and thus reveal the potential relationships between the data. In general, unsupervised learning is not appropriate for financial predictive analysis because most of the predictions are based on historical value. Other statistics, such as structural models or analytical hierarchy processes (AHP) (Hogan 2000), are also

[1]Illustrative references for application of techniques: SVM (Hua et al. 2007); ANN (Zhang et al. 1999); genetic algorithm (Duman and Ozcelik 2011); C4.5 (Foster and Stine 2004); BBN (Kirkos et al. 2007)

available as business analytics techniques for management accountants to provide estimation of future financial performance of a company.

With the results of descriptive and predictive analytics, management accountants can utilize prescriptive business analytics to recommend the optimal solutions and their likely outcomes. While prescriptive analytics share the similar techniques and algorithms as predictive analytics, prescriptive analytics essentially compare the result of such algorithms and aim to find the optimized solution. For example, to reduce cost and at the same time maintain the product quality in a reasonable area for generating revenue, manufacturing companies face the challenge of selecting the raw material vendors with a reasonable price and appropriate quality. Incorporating the results generated from analyzing internal data together with data from vendors using SVM, ANN, or C4.5 classifiers, prescriptive analytics help management accountants to choose the vendor that will help the company to reduce cost and increase revenue. For example, data from news articles and social media can also be used in the selection of a vendor. Besides cost reduction, with prescriptive analytics management accountants are also able to provide valuable information on other issues in the financial perspective, such as exploring new markets, new products, and new customers.

Customer Perspective

The customer perspective of BSC answers the question of “How do customers see us?” In the original BSC framework, Kaplan and Norton (1992) describe the customers’ concerns from four categories: time, quality, performance and service, and cost. Time refers to the time required for the company to meet customers' needs. Quality measures the customers' perceived defect level of products or service. The combination of performance and service measures how the company's products or services contribute to creating value for the customers. Finally, cost measures the price to the company of reaching certain level of previous measures. The customer perspective stands as the primary goal of most non-for-profit organizations and government departments. Non-profit and government organizations generally have financial donors or other funding. The primary goal for them is to satisfy their customers and achieve progress in designated missions. It is the mission, rather than the financial/shareholder objectives, that drives the organization's strategy (Kaplan and Norton 2001).

Descriptive business analytics provide a comprehensive view of the current situation of customer measures from the BSC. For instance, a ratio analysis that integrates product defect rate, goods returned rate, and warranty claim rate can be used to measure the customer's satisfaction level about the latest product of a manufacturing company. Data analytics also enables management accountants to incorporate customer ratings from websites and reviews or complaints from the product forum. Techniques such as text mining allow users to extract opinions from online text content (e.g., twitter feeds) and generate useful information. While most business analytics require structured data sources, text mining and visualization allow management accountants to extract decision-related information from unstructured data such as social media data.

With predictive business analytics, management accountants are able to provide reasonable estimates of each of the four aspects of the customer's perspective of a company’s products or services. Specifically, time, quality, performance and service, and cost can be estimated using internal historical data or external website or social media data through predictive analytics algorithms (e.g., SVM, ANN, genetic algorithms, BBN, log regression, time series regression, structural models, analytical hierarchy processes and Monte Carlo study/simulation). For example, management accountants could use a business analytic tool that trains the ANN model with internal data to predict the time period between the point that the company receives the customer’s order and the point that the product or service is delivered. This would help coordinate the cooperation among different company departments and to assist managers adjust company strategies accordingly. (Tuarob and Tucker 2013) utilize text mining techniques to analyze social media data (e.g. twitter feeds) to predict information related to product features, product competition and market adoption.

Prescriptive business analytics provides the optimal solution between corporate cost and the first three factors– time, quality, and performance and service– of the customer perspective. The corporation usually emphasizes ongoing improvement with customer satisfaction, which entails faster response to customers’ requests, higher product quality, and better performance and service, all while facing budget constraints. Management’s strategy of capital and labor input to improve customer satisfaction and loyalty can be a set of complex decisions. By incorporating various types of descriptive and predictive analytics, management accountants can provide decision-related information to management to answer questions like “Does our measurement method of customer satisfaction reveal the truth?”; “Which customer performance enhancement will lead to the highest return in revenue?"; and "Who will be our potential customers?". The availability of efficient analysis techniques (e.g. text mining) and real time social media data (e.g. twitter data) enables management accountants to perform analysis on-the-fly and to assist management with forming appropriate customer perspective related strategy. As Kaplan (2008) points out, to differentiate from their competitors, companies need to express objectives for the value proposition they offered to the customers. The value proposition includes price, quality, availability, ease and speed of purchase, functionality, relationship, and service. Rather than considering each component individually, management accountants can employ prescriptive analytics techniques, such as artificial neural networks and linear regression, to analyze how such components affect the customer measurement simultaneously.

Internal Process Perspective

The internal process perspective of BSC measures the business process by factors that affect cycle time, quality, employee skills, and productivity (Kaplan and Norton 1992). To apply the measurement effectively, management accountants must decompose the overall cycle time, quality, employee skills, and productivity from department and workstation levels to local levels, which provides lower level employees a clear target for actions, decisions, and improvements. Information systems provide an important communicating role between management accountants and the corporate workforce. A well functioned responsive information system provides management accountants valuable "in time information" which can be presented to the managers for decision making.

The current condition of internal processes can be summarized with descriptive analytics. The clustering technique in descriptive analytics could be utilized to identify highly efficient employees by combining measurement of employee skills, productivities, and other characteristics of the employees. On the other hand, text mining can be used to identify employees that go astray against the company. For example, Holton (2009) uses text mining to identify disgruntled employees from email text. In addition to traditional measurement of the overall cycle time, quality, employee skills, and productivity proposed by Kaplan and Norton (1992), process mining provides management accountants an overview and understanding of the flows of process within the entity. For example, using event logs provided by ERP systems, process mining can be used to extract workflow processes (Van der Aalst et al. 2004), which can be integrated with visualization techniques to provide a comprehensive illustration of the work processes that are taking place within the organization.

Predictive analytics play an important role in measuring and managing internal processes. Based on historical data, management accountants can utilize predictive analytics tools to build models to predict future values of the related areas of the four main measurements and thus providing the benchmark for monitoring. If management accountants identify that the actual performance is significantly worse than the predicted result, then they would need to decide whether this deficiency is either caused by poor performance (e.g. deficiency in internal control) or by an inappropriate model selection. The prediction model sometimes deteriorates if not properly maintained. For instance, as the business operation becomes more complex, factors that have significant impact on internal process may not be included in the original prediction model. Thus, predictive analytics tools should be continuously monitored and modified to ensure the usefulness of prediction results. An example of implementing predictive analytics in the internal process perspective is to apply process mining to optimize enterprise transactions. Management accountants can use process mining to understand the flows of transactions and predict process efficiency in various situations. Based on such information, management can modify routine processes to achieve organizational efficiency. In addition, making predictions of possible future events helps management accountants to reduce the possibility of contingencies. Specifically, management accountants can provide the predictive report to all levels of employees of the company so that each individual employee will have a broader understanding of the current and expected internal process of the company.

Prescriptive analytics aim to provide optimization of internal processes based on the analysis results from descriptive and predictive analytics. For example, for a company that emphasizes productivity, management accountants can use prescriptive analytics to find the optimal solution among employee skills, transaction processing complexity, and production quality. Traditionally, complicated decisions are made based on experience and simple descriptive statistics. With prescriptive analytics tools, management accountants can provide decision makers more specific decision related information that are extracted through statistics and models. For the internal process perspective in BSC, techniques such as goal programming (Lin 1979) or Pareto optimization (Cushing 1977) can be used in prescriptive analytics to transform the complicate decision making process to optimization models that include information provided by descriptive and predictive algorithms from other different perspectives.

Learning and Growth Perspective

To answer the question of "Can we continue to improve and create value", the learning and growth perspective measures the company's ability to innovate, improve, and learn that ties directly to the company's value (Kaplan and Norton 1992). Specifically, it measures the company's ability to launch new products, create more value for customers, and continually improve operating efficiencies. Such measurements align human resources and information technology with the strategic requirements from the company's critical internal business processes, differentiated value propositions, and customer relationships (Kaplan and Norton 2001). Examples of learning and growth perspective measurements include, for example, market share of new products and employees training expenses.

Learning and innovation are critical in almost every company. The conditions of learning and innovation can be interpreted both as developing new products or services and adopting new technologies. Descriptive analytics can be used as tools that demonstrate how much emphasis companies put on innovation and how the employees are learning to work with new challenges. For instance, the ratio of research and development expense to the total expense can be used to describe how much the company is focusing on developing new products or services. On the other hand, visualization and text mining methods can be used to evaluate the progress of learning. Chand et al. (2005) indicates in a case study that the implementation of ERP systems requires 4-5 weeks of training with the users. Thus, descriptive business analytics tools that exhibit the progress of learning of new systems enable the management accountants to monitor the progress of adopting new technologies.

Predictive analytics is an essential part of measuring the learning and growth perspective. As both innovation and learning focus on the future benefits, it is imperative to know the possible outcome of current investments in innovation and employee training. Predictive algorithms such as SVM, ANN, time series regression and probability theory models can all be trained to predict results. In addition, expert systems and decision aids help management accountants to understand specific situations and to provide stimulated estimation accordingly.

Prescriptive business analytic tools help management accountants to integrate descriptive and predictive analytics in the learning and growth perspective and find the optimized strategy or direction. Machine learning algorithms included in prescriptive analytics techniques are used to train models for the purpose of taking an innovation perspective into consideration with other factors such as customer satisfaction and revenue of sales, and identifying the optimized strategy to improve the design of a new version of smart phones. Management accountants also can use prescriptive analytics to decide which new technology to incorporate to increase productivity and work efficiency. Choices of ERP vendors such as Oracle and SAP can be decided through analyzing news and customer reviews from websites or social media.

Table 8 provides a summary of applications of data analytics techniques in managerial accounting from the BSC perspective. Three types of data analytics techniques, descriptive, predictive, and prescriptive, are implemented into the four perspectives of BSC framework. The check mark indicates whether the technique is considered applicable for the specific BSC perspective. For example, the "ratio analysis" technique under the descriptive category is appropriate for applications in financial, customer, and learning and growth perspectives. While the selection of the appropriate techniques is an important factor for successful implementation of data analytics in managerial accounting, other factors, such as consideration of business intelligence context, data integrity, and privacy, are also critical determinants of effective applications.

Table 8: Implementation of Data Analytics Techniques in BSC Perspectives

Descriptive	Financial	Customer	Internal Process	Learning and Growth
Clustering Models		✓	✓	✓
Descriptive Statistics	✓	✓	✓	✓
Process Mining: Process Discovery Models			✓	
Ratio Analysis	✓	✓		✓
Spearman Rank Correlation Measurement	✓	✓	✓	✓
Text Mining Models		✓	✓	✓
Visualization	✓	✓	✓	✓
Predictive	Financial	Customer	Internal Process	Learning and Growth
Analytical Hierarchy Processes (AHP)		✓		
Artificial Neural Networks (ANN)	✓	✓	✓	✓
Auto Regressive Integrated moving Average	✓	✓	✓	✓
Bagging and Boosting models	✓	✓	✓	✓
Bayesian Theory/Bayesian Belief Networks	✓	✓	✓	✓
Benford's Law	✓	✓	✓	✓
C4.5 Statistical Classifiers	✓	✓	✓	✓
Dempster-Shafer Theory Models	✓	✓	✓	✓
Expert Systems/Decision Aids			✓	✓
Genetic Algorithms	✓	✓	✓	✓
Hypothesis Evaluations	✓	✓	✓	✓
Linear Regression	✓	✓	✓	✓
Log Regression	✓	✓	✓	✓

Monte Carlo Study/Simulation	✓	✓	✓	✓
Multi-criteria Decision Aid	✓	✓	✓	✓
Probability Theory Models	✓	✓	✓	✓
Process Mining: Process Optimizations			✓	
Structural Models	✓	✓	✓	✓
Support Vector Machines (SVM)	✓	✓	✓	✓
Time Series Regression	✓	✓	✓	✓
Univariate and Multivariate Regression	✓	✓	✓	✓
Prescriptive	Financial	Customer	Internal Process	Learning and Growth
Artificial Neural Networks (ANN)	✓	✓	✓	✓
Auto Regressive Integrated Moving Average	✓	✓	✓	✓
Expert Systems/Decision Aids	✓	✓	✓	✓
Genetic Algorithms	✓	✓	✓	✓
Linear Regression	✓	✓	✓	✓
Log Regression	✓	✓	✓	✓
Monte Carlo Study/Simulation	✓	✓	✓	✓
Time Series Regression	✓	✓	✓	✓
Univariate and Multivariate Regression	✓	✓	✓	✓

4.5 CRITICAL SUCCESS FACTORS FOR MADA IMPLEMENTATION

4.5.1 Business Intelligence (BI) Context

Management accounting tasks as described in the MADA framework could be regarded as an essential component of Business Intelligence (BI). A successful application of MADA could largely rely on its seamless integration within the overall BI system and its ability to contribute meaningful insights. BI has been largely described as "as set of techniques and tools for the acquisition and transformation of raw data into meaningful and useful information for business analysis purposes" (Turner 2016). Business Intelligence as such may be considered as the management support system for gathering, storing, accessing, and analyzing data for decision making (Chaudhuri et al. 2011). It would be difficult to find a business with extensive data sources and enterprise system capacities that is not leveraging these assets to realize a competitive advantage (Davenport 2006).

Research results indicate that investment by businesses in BI infrastructure and functionality is associated with increased competitive advantage (Peters et al. 2016). Davenport (2006) discusses how BI forces businesses to evolve to fact-based decision making from that of intuitive decision making. Watson and Wixom (2007) relate the benefits of BI systems to date, which include time savings, improved information and business processes, and improved strategic decisions. Management accounting tasks in the modern business enterprise fall neatly as an essential component of BI functionality. Since BI software is a "collection of decision support technologies for the enterprise aimed at enabling…executives, managers, and analysts to make better and faster decisions" (Chaudhuri et al. 2011), the management accountant's task of providing analyses and forecasts to management requires usage of BI components. Hence, the management accountant would also be expected to leverage big data and the capacity of BI systems to support the use of advanced analytics. Successful implementation of the MADA framework depends on its success as a component of a holistic enterprise-wide BI system (Figure 8).

The past few decades have seen explosive growth in the use of BI by enterprises, particularly regarding the value and success factors involved with such BI integration (Fink et al. 2016). Several papers (Yeoh and Koronios 2010; Yeoh and Popovič 2016) formalize critical success factors (CSFs) for the implementation of BI (DeLone and McLean 1992, 2003). Delone and McLean (2003) propose that the measurement of any IS success be based on the research objectives and IS context. As such, Yeoh and Koronios (2010) apply the domain of BI to the IS success and BI literature to develop a BI Critical Success Factors (CSF) framework (Table 9).

Figure 8: Ideal Enterprise System Structure that Supports Management Accountants in a BI System

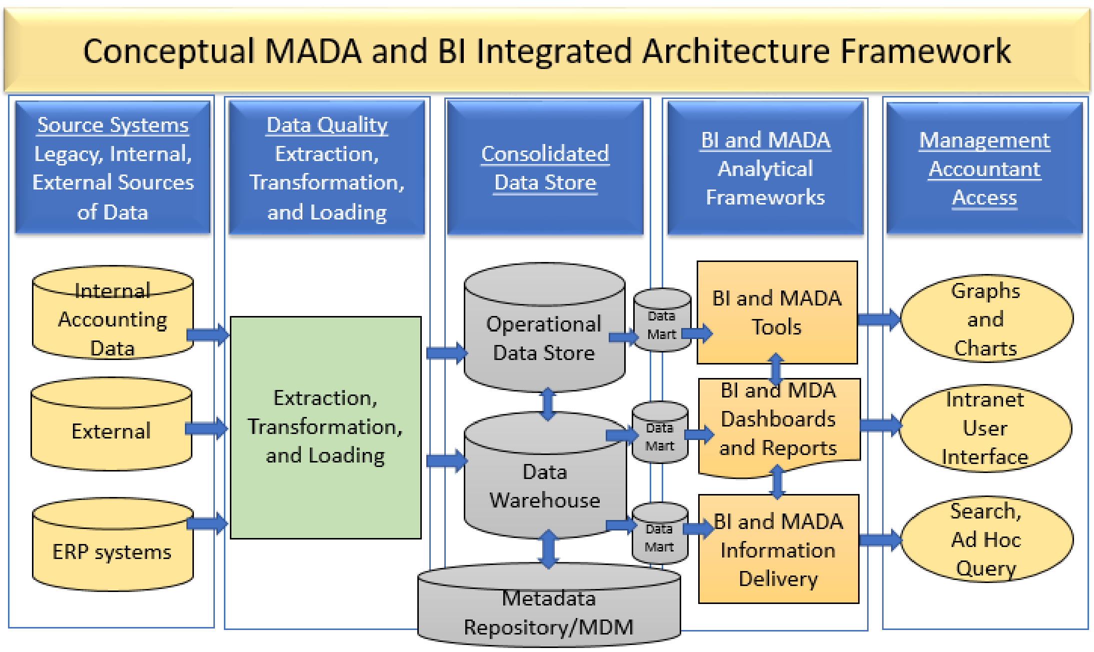


Figure 8 is motivated from Chaudhuri et al. (2011)

Table 9: Three Main Dimensions of CSFs for BI

Dimension	**Critical Success Factors (CSF)**
Organization	Committed management support and sponsorship
	A clear vision and well-established business case
Process	Business-Centric championship and balanced project team composition
	Business-driven and iterative development approach
	User-oriented change management
Technology	Business-driven, scalable and flexible technical framework
	Sustainable data quality and integrity

Table 9 is summarized from (Yeoh and Koronios 2010; Yeoh and Popovič 2016)

The two most dominant CSFs for management accountants would be: one, a business driven, scalable, and flexible technical framework; and two, sustainable data quality and integrity. Both CSFs are the focus of this paper. However, the success of any projects undertaken by the management accountant could be impacted by the other CSFs as well. The CSF framework of Table 9 is expanded here to describe the CSFs for Managerial Accounting in the BI domain (Table 10).

Table 10: The CSRs for Managerial Accounting in the BI Domain

Dimension	**Critical Success Factors (CSF)**
Organization	Committed management support and sponsorship for more advanced analytics and the necessary infrastructure to support these initiatives
	A clear vision and well-established understanding of the business case and domain of the business and industry.
Process	Business-Centric championship and balanced project team composition with support from IT staff
	Business-driven and iterative development approach with frequent feedback of incremental results
	User-oriented change management where scope and functions of management accounting processes evolve to the new enterprise paradigm
Technology	Business-driven, scalable, and flexible technical framework that is capable of handling big data and many varied analytics and data mining techniques
	Sustainable data quality and integrity of big data that is enforced with a master data approach and with which the management accountant is familiar

Table 10 is adopted from Yeoh and Popovič (2016)

4.5.2 CSF: Business-Driven, Scalable, and Flexible Technical Framework

Data delivers limited value to management accountants unless they can access it and use it to provide analysis and projections for management (Watson and Wixom 2007).

Data is often regarded as a highly valuable asset of an organization (Chugh and Grandhi 2013). This value can be realized as a competitive advantage for the organization if the appropriate BI tools, expanded data sources and appropriate systems are in place (Chugh and Grandhi 2013). Major software vendors such as SAP, Oracle, IBM, and Microsoft have developed ETL and BI tools and applications, all which should contain the functions listed in Table 11 to assist the management accountant:

Table 11: BI Functionalities to Support the Management Accountant

Categories	**Function**
Data Consolidation	➢ Integration of internal and external data ➢ Simplified extraction, transformation, and loading of data ➢ Deletion of unwanted and unrelated data
Data Quality	➢ Sanitize and prepare data to improve overall accuracy
Reporting	➢ User defined and standard reports generated at any level ➢ Personalized reports for any level of management
Forecasting and Modelling	➢ Supports analytics used in predictive and prescriptive analytics which use historical and real-time data, qualitative or quantitative
Tracking of real-time data	➢ Monitor current progress with defined project objectives/KPIs ➢ Prioritize scarce system resources
Data visualization	➢ Interactive reports and graphics, possibly with real time updates ➢ Scorecards and dashboards
Data analysis	➢ What-if analysis ➢ Sensitivity/optimization analysis ➢ Goal seeking/goal supporting analysis ➢ Descriptive analysis
Mobility	➢ Portability to multiple devices and formats
Rapid Insight	➢ Drill down features that enable many layers of analysis ➢ Dashboards that are interactive and that can monitor trends and outcomes
Report Delivery & Share-ability	➢ Deliver reports in common formats such as Microsoft Office ➢ Email reports in different formats
Ready to Use applications	➢ Pre-built meta-data with mappings defined considering performance & security needs ➢ Pre-built reports, dashboards to support management
Language Support	➢ Multiple language support

Table 11 is adopted from Chugh and Grandhi (2013)

The steps of Data Consolidation and Data Quality are not specified in the MADA framework as conceptualized in Figure 7 but are usually part of most corporate enterprise systems. Like other analytical functions in the enterprise, MADA relies on the system processes and functions to provide quality data. Conceptually, MADA could be integrated in an enterprise BI system similar to that portrayed in Figure 8.

The MADA framework is envisioned to be integrated at the same level in the system as the other BI applications (Figure 8). The source systems are where all the business events and transactions take place, either inside or outside to the system. In MADA (Figure 7), this is depicted in the upper left hand quadrant as external and internal big data. But this data is varied and messy, so it needs to be extracted, transformed, and loaded (ETL) before it can be stored or analyzed. This ETL process creates consolidation, consistency, convenience, and referential integrity of the data. This allows the third process of data storage in the enterprise system to occur, where data can be integrated with meta tags. Data Marts serve to facilitate the data for a particular MADA or BI analysis. The Data Marts contain a semantic layer (fourth layer) which allows for MADA and business analytics to occur. The last layer allows for multiple ways for management accountants to consume the information provided by MADA at the previous layer.

4.5.3 CSF: Sustainable Data Quality and Integrity and Big Data

Data quality and integrity are recognized as essential components of a business analytics system (Cosic et al. 2012; Chae and Olson 2013). Data quality is also an essential element of any enterprise system (Xu et al. 2002; Chae and Olson 2013; Kwon et al. 2014) and its architecture. However, as data volumes increase, the more the complexity of data management increases. As the type of data format varieties increase, so does the flexibility demands of managing it (Kwon et al. 2014). The greater the data velocity speed, the more capacity is required of the system. The more varied the data veracity becomes, the greater the demands for system assurance and controls. With the Four V's of big data, the risk of poor quality information to businesses increases (Watts et al. 2009; Wu et al. 2014).

The impact of poor quality data has been identified in numerous academic studies (Wu et al. 2014; Yeoh and Koronios 2010; Watson and Wixom 2007) and these concerns are magnified with big data. Poor quality data that was not identified as such, but was used instead to generate market predictions, forecasts, and other analyses, could have substantial negative economic impact on a business (Haug and Stentoft Arlbjørn 2011). These negative effects on profits may be felt in the marketplace, in the operations, in the business performance, and in the business culture.

Available software applications analyze the datasets for internal and external validity, accuracy, timeliness, completeness, and consistency. The most basic challenge of big data applications with analytics is the exploration of the big data and the subsequent extraction of useful information for the analytical application. Typically, big data is heterogeneous and of varied formats and requires preparation before analysis. Also, the data extraction process needs to very efficient and as close to real time or continuous as possible because storage of big data could be infeasible (Wu et al. 2014).

Two secondary concerns include 1) data sharing and privacy/security; and 2) domain and application specific knowledge. The first is more challenging then the second, as management accountants usually possess a thorough understanding of the enterprise's business orientations and culture. The concerns of data privacy and security that result from the sharing and integration of many different data types from varying origins is the greater challenge. Data privacy may be an issue with any reports involving employee and customer information. Information acquisition, sharing, and integration are the goals when the management accountant is combining different big data sources. If some of this data involves personal or sensitive information, disclosure of a person's actions/locations over time could be compromised even with data security and privacy measures. Two typical approaches for privacy maintenance are data access restriction and data anonymization (Cormode and Srivastava 2009), controls which should be enforced system-wide. Data security is an enterprise wide concern, with controls and procedures established by the IT department and the management accountant needs to ensure that the controls and procedures are followed.

4.6 CONCLUSION AND FUTURE WORK

The role of managerial accounting is evolving from the traditional emphasis on financially oriented decision analysis and budgetary control to a more strategic approach that emphasizes the identification, measurement, and management of the key financial and operational drivers of shareholder value (Ittner and Larcker 2001). With the developments in enterprise systems that provide management accountants access to more data and data types, larger data storage, and better computational power, enterprise systems that incorporate this additional data now can utilize data analytics techniques to answer the questions including: what has happened (descriptive analytics), what will happen (predictive analytics), and what is an optimized solution (prescriptive analytics). However, research shows that the nature and scope of managerial accounting has not developed to take advantage of such techniques (Sangster et al. 2009). This situation is not unique to managerial accounting – according to Van Der Meulen (2016), the number one issue for businesses that have invested in big data is determining exactly how to get value or information from this data.

This paper first examines the impact of enterprise systems, big data, and data analytics on managerial accounting. Second, the managerial accounting data analytics (MADA) framework is proposed for management accountants to utilize data analytics in the environment of enterprise systems. The MADA framework implements data analytics techniques based on the balanced scorecard (BSC) theory. Descriptive, predictive, and prescriptive analytics are applied to measure corporate performance from four aspects: financial, customer, internal process, and learning and growth. Data analytics are also a key component in the feedback and learning process when company designs a strategic management system based on BSC theory. Finally, attributes for successful implementation of the MADA framework are discussed. Data analytics and managerial accounting tasks as described in the framework could be regarded as essential components of Business Intelligence (BI). The analytical technique(s) selected by the accountant should not only be appropriate, but the data or big data selected for analysis should possess high quality attributes such as relevance, timeliness, and accuracy, to ensure the usefulness of the information generated through the analytics.

One major challenge facing the MADA framework is how it could be tested. Ideally, with MADA serving as methodological guideline, the framework could be applied as a case study within a company's actual enterprise system. With such a case study, researchers could then determine whether the proposed benefits can be achieved and how these should be measured. Furthermore, a greater understanding of the enterprise and corporate system changes that would be required for a successful MADA implementation can be acquired. However, gaining access to such a case study situation usually presents major challenges for researchers – typically, companies are reluctant to allow outsiders access to internal enterprise systems and data.

Due in part to the utilization of enterprise systems by business, the methodology of continuous monitoring (Alles et al. 2006; Vasarhelyi et al. 2004), facilitated by the progressive decrease of computation and storage costs, is emerging. In this progressive scenario, the fact that the incremental cost of repeating analytic procedures is low allows a more frequent (not exactly continuous) application of analytic procedures and consequently better managed/ monitored processes. Research is needed to develop a framework for the timing, frequency, management, and measurement needed for this manner of analytic application.

Another challenge facing the MADA framework is obtaining greater clarification and detailed analysis of when, where, and under what circumstances certain analytics should be undertaken. That is, given a broad understanding of the techniques categorized in Table 7, the context of a certain industry, the scope of the managerial accounting task required, and the type of available data, what would be the best technique(s) from the framework to apply and how would these approaches measure against current managerial accounting practices? Such a comparison should be examined not only in the context of prediction accuracy but also of feasibility. For example, perhaps theoretically an artificial intelligence application might provide the greatest prediction accuracy for a cost analysis of delivery routes for a firm; but practically, a predictive regression model may be more feasible even though the accuracy level might be somewhat lower. Fortunately, comparing the performance and feasibility of such individual MADA applications to that of current managerial accounting practices is a less prohibitive task for researchers than that of a case study.

A third challenge facing MADA integration would be that of the analytical skills and knowledge acquisition required by management accountants to successfully apply it. Many currently practicing management accountants may not possess extensive knowledge of analytics and big data. Would training or course work be provided by commercial ERP providers if MADA is offered commercially? Or, would companies support or encourage training in analytics by funding their accountants to take online /on-campus courses offered by universities? And for future accountants, would university programs offer more possibilities for analytics and big data courses? These are challenges facing the field of accounting and auditing in general, as businesses migrate towards the use of more technology, analytics, and big data.

This paper presents the MADA framework, which implements data analytics techniques based on BSC theory in an enterprise system environment. Currently, the scope and processes for managerial accounting tasks are challenged by the enormous potential that these expanded enterprise systems, big data, and analytics present. Integrating MADA in such an environment could provide huge possibilities for management accountants to overcome these complexities and subsequently evolve to a new expanded level. This paper presents the theoretical framework that discusses the important elements and proposed design of MADA. Ideally, the MADA framework and its proposals should be researched empirically before it would be applied as a case study in the managerial accounting domain.

CHAPTER 5: CONCLUSION AND FUTURE RESEARCH

This dissertation contributes to accounting research by investigating the process of the adoption of disruptive innovations by auditors and proposing frameworks for implementing two specific emerging technologies in auditing and managerial accounting domain. The major findings and future works of the three essays are summarized as follows.

The first essay attempts to incorporate the disruptive innovation concept (Christensen 1997) in understanding the adoption process of disruptive innovations in audit domain. A disruptive innovation can potentially impact audit procedures at two levels, technology level and methodology level. Specifically, technology level disruption can affect technologies adopted for current audit procedures or create new types of audit procedures, while methodology level disruption could change the fundamentals of the audit process. This essay further points out that sustaining innovations are adopted and developed within audit practice, whereas disruptive innovations are developed by external parties because they cannot be directly adopted by auditors. The disruption occurs when an emerging technology or methodology becomes accepted by audit regulations and adopted in the audit practice. Further improvements on the adopted disruptive innovations become sustaining innovations.

The first essay contributes to the auditing literature from in aspects. Firstly, this study provides the definition for sustaining and disruptive innovations in the auditing domain. Furthermore, several emerging technologies are classified based on their potential disruptive levels. This essay provides a feasible solution to use disruptive innovation theory to explain the adoption of data analytics in auditing as proposed by Alles (2015), and expands the TPR theory proposed by Issa et al. (2016). Secondly, this study demonstrates the distinct processes of how sustaining and disruptive innovations are adopted by auditors. The proposed framework can be utilized to assist practitioners, researchers, and regulators to obtain better understandings of the technology adoption in the auditing domain. Most of the prior literature that examines audit technology adoption focuses on technology adoption models such as UTAUT (Payne and Curtis 2008; Gonzalez et al. 2012; Curtis and Payne 2008; Janvrin et al. 2008a; Janvrin et al. 2008b; Bierstaker et al. 2014). This essay adds to the literature by incorporating the disruptive innovation theory in investigating the technology adoption by auditors.

The first essay also enables opportunities for future study. To begin with, this study does not include a detailed discussion of disruptive innovations at the transformation stage. Disruption can be a process rather than a single moment (Christensen 1997). Therefore, there can be a transforming stage in which a disruptive technology gradually becomes accepted by auditors and regulators. Future research can examine this process to better understand disruptive innovations in audit. Secondly, this essay only examines a limited number of emerging disruptive technologies. Future research can apply the theory provided in this essay to investigate more emerging technologies in auditing. Lastly, the proposed conceptual framework is solely based on theories and conclusions from prior literature. Future research can conduct behavioral experiments or surveys to test the proposed framework, and empirically compare the proposed framework to other technology adoption model in auditing domain.

The second essay focuses on proposing the contract analytics framework (CAF) to incorporate NLP and text mining techniques to provide automation suggestions and guidance to auditors for investigation of populations of contracts with low perceived risks. The proposed CAF contains six functional areas for auditors to perform contract-related audit tasks on the entire population of contracts. The essay also implements CAF on a small sample of reinsurance contracts to demonstrate the feasibility of auditors to utilize NLP to extract audit-related content, detect value and text-based anomalies, and generate audit evidence.

The contribution of essay two is twofold. First, this study demonstrates through CAF that NLP and text mining techniques can be incorporated into contract related audit procedures to provide auditors with additional data for the assessment of audit risk and creation of audit evidence. With CAF, auditors could be free from repetitive contract examinations and spend more time to handle higher level data. In addition, auditors can utilize CAF to perform audit procedures on contracts that are too cumbersome to audit with the traditional method. Second, the CAF framework is mapped to current auditing standards to provide automation suggestions to audit tasks and increase the reliability of the analyses.

There are also several limitations in this study. First, the testing data is limited to one set of similar contracts. The implementation would be more informative if multiple sets of similar contracts or customized contracts are involved in the process. The implementation is based on a small sample of contracts, which precludes the opportunity to perform the promoted population-wide data analytic functions. Future research can test

CAF on a large sample. Second, the results could be affected by low quality of the PDFs. The low quality image can lead to high number of errors when using OCR to digitize texts. The erroneous data extracted from the contracts can make functions such as cutoff testing, record confirmation, and term verification unusable. In this situation, auditors have the choice to manually correct the errors, to rely on the client's database, or revert to sampling methods. Although the sample size is small, and the PDFs are of variable quality, the implementation helps demonstrates the feasibility of the framework.

The third essay first examines the impact of enterprise systems, big data, and data analytics on managerial accounting. Then, this study proposes the MADA framework for management accountants to apply data analytics in the enterprise systems environment. The implementation of data analytics techniques is based on the BSC theory. Three types of data analytics (i.e., descriptive, predictive, and prescriptive) are applied to measure corporate performance from four aspects: financial, customer, internal process, and learning and growth. Additionally, attributes for the successful implementation of the MADA framework are also discussed. The analytical techniques implemented should not only be appropriate, but the data selected for analysis should also possess high quality attributes such as relevance, timeliness, and accuracy, to ensure the usefulness of the information generated through the analytics.

The third essay contributes to the literature in several ways. First, this study discusses from an enterprise system perspective the impact of business analytics on managerial accounting. Although prior literature has proposed a BSC framework for management accountants to implement business analytics (Nielsen 2015; Silvi et al. 2010), few have considered this issue under the enterprise systems context. Second, this study proposes the MADA framework for management accountants to implement data analytics for corporate performance measurement under the BSC perspective. Lastly, factors related to the implementation of the MADA framework are discussed to connect the MADA framework to modern business practice.

There are also limitations and challenges associated with essay three. One major challenge is related to how the MADA framework can be tested. Future research can apply the framework in the form of a case study within a company's enterprise system. Researchers could then examine how the proposed benefits can be achieved and measured. Another challenge facing the MADA framework is to provide better clarification of the criteria of deciding which type of analytics should be undertaken. This issue should be examined both in the context of prediction accuracy and feasibility. The third challenge confronting MADA integration would be the analytical skills and knowledge acquisition required by management accountants before they can successfully apply data analytics. Current management accountants may not possess extensive knowledge of analytics and big data. Future research can be conducted to see whether providing training could improve MADA implementation. As businesses migrate towards the use of more technology, education on business analytics would be a challenge to the profession.

BIBLIOGRAPHY

Agarwal, R., and J. Prasad. 1997. The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision sciences* 28 (3):557-582.

Aguirre, S., and A. Rodriguez. 2017. Automation of a business process using robotic process automation (rpa): A case study. Paper read at Workshop on Engineering Applications.

AICPA, A. I. o. C. P. A. 1976. AU Section 337. Inquiry of a Client's Lawyer Concerning Litigation, Claims, and Assessments. Available at: https://pcaobus.org/Standards/Auditing/Pages/AU337.aspx.

———. 2002. AU Section 316. Consideration of Fraud in a Financial Statement Audit. Available at: https://pcaobus.org/Rulemaking/Docket038/Release_2014_002_Related_Parties.pdf.

———. 2003a. AU Section 328. Auditing Fair Value Measurements and Disclosures. Available at: https://pcaobus.org/Standards/Auditing/pages/au328.aspx.

———. 2003b. AU Section 342. Auditing Accounting Estimates Available at: https://pcaobus.org/Standards/Auditing/Pages/AU342.aspx.

———. 2008. AU Section 350. Audit Sampling. Available at: https://pcaobus.org/Standards/Auditing/pages/au350.aspx.

———. 2010. AU Section 319. Consideration of Internal Control in a Financial Statement Audit. Available at: https://pcaobus.org/Standards/Archived/Pages/AU319.aspx.

Alles, M., G. Brennan, A. Kogan, and M. A. Vasarhelyi. 2006. Continuous monitoring of business process controls: A pilot implementation of a continuous auditing system at Siemens. *International Journal of Accounting Information Systems* 7 (2):137-161.

Alles, M. G. 2015. Drivers of the use and facilitators and obstacles of the evolution of big data by the audit profession. *Accounting Horizons* 29 (2):439-449.

Alles, M. G., A. Kogan, and M. A. Vasarhelyi. 2002. Feasibility and economics of continuous assurance. *Auditing: A Journal of Practice & Theory* 21 (1):125-138.

Alles, M. G., A. Kogan, and M. A. Vasarhelyi. 2008. Putting continuous auditing theory into practice: Lessons from two pilot implementations. *Journal of Information Systems* 22 (2):195-214.

Anandarajan, M., and A. Anandarajan. 1999. A comparison of machine learning techniques with a qualitative response model for auditor's going concern reporting. *Expert Systems with Applications* 16 (4):385-392.

Appelbaum, D. 2017. Public auditing, analytics, and big data in the modern economy, Rutgers University.

Appelbaum, D., A. Kogan, and M. A. Vasarhelyi. 2016. Analytics in External Auditing: A Literature Review. Working Paper. *Rutgers University CARLab, Newark NJ, USA*.

Appelbaum, D., A. Kogan, and M. A. Vasarhelyi. 2017. Big Data and analytics in the modern audit engagement: Research needs. *Auditing: A Journal of Practice & Theory* 36 (4):1-27.

Appelbaum, D., and R. Nehmer. 2017a. Designing and Auditing Accounting Systems Based on Blockchain and Distributed Ledger Principles. *Feliciano School of Business*.

Appelbaum, D., and R. A. Nehmer. 2017b. Using drones in internal and external audits: An exploratory framework. *Journal of emerging technologies in Accounting* 14 (1):99-113.

Appelbaum, D. A., A. Kogan, and M. A. Vasarhelyi. 2018. Analytical procedures in external auditing: A comprehensive literature survey and framework for external audit analytics. *Journal of accounting literature* 40:83-101.

Ayata. 2012. The Evolution of Big Data Analytics. http://ayata.com/the-evolution-of-big-data-analytics/.

Baeza-Yates, R., and B. Ribeiro-Neto. 1999. *Modern information retrieval*. Vol. 463: ACM press New York.

Basu, A. 2013. Five pillars of prescriptive analytics success. *Analytics Magazine*:8-12.

Bertsimas, D., and N. Kallus. 2014. From predictive to prescriptive analytics. *arXiv preprint arXiv:1402.5481*.

Bierstaker, J., D. Janvrin, and D. J. Lowe. 2014. What factors influence auditors' use of computer-assisted audit techniques? *Advances in Accounting* 30 (1):67-74.

Birnberg, J. G. 2009. The case for post-modern management accounting: Thinking outside the box. *Journal of Management Accounting Research* 21 (1):3-18.

Bishop, C. M. 2006. *Pattern recognition and machine learning*: springer.

Blei, D. M., A. Y. Ng, and M. I. Jordan. 2003. Latent dirichlet allocation. *Journal of machine Learning research* 3 (Jan):993-1022.

Brands, K. 2015. Business Analytics: Transforming the Role of Management Accountants.

Brown-Liburd, H., and M. A. Vasarhelyi. 2015. Big Data and audit evidence. *Journal of emerging technologies in Accounting* 12 (1):1-16.

Brown, C. E., J. A. Wong, and A. A. Baldwin. 2007. A review and analysis of the existing research streams in continuous auditing. *Journal of emerging technologies in Accounting* 4 (1):1-28.

Brynjolfsson, E., and A. Mcafee. 2017. The business of artificial intelligence. *Harvard business review*.

Byrnes, P. E., A. Al-Awadhi, B. Gullvist, H. Brown-Liburd, R. Teeter, J. D. Warren Jr, and M. Vasarhelyi. 2018. Evolution of Auditing: From the Traditional Approach to the Future Audit 1. In *Continuous Auditing: Theory and Application*: Emerald Publishing Limited, 285-297.

Cao, M., R. Chychyla, and T. Stewart. 2015. Big Data analytics in financial statement audits. *Accounting Horizons* 29 (2):423-429.

Card, M. 1999. *Readings in information visualization: using vision to think*: Morgan Kaufmann.

Cecchini, M., H. Aytug, G. J. Koehler, and P. Pathak. 2010a. Detecting management fraud in public companies. *Management science* 56 (7):1146-1160.

———. 2010b. Making words work: Using financial text as a predictor of financial events. *Decision Support Systems* 50 (1):164-175.

Chae, B., and D. L. Olson. 2013. Business analytics for supply chain: A dynamic-capabilities framework. *International Journal of Information Technology & Decision Making* 12 (01):9-26.

Chae, B. K., C. Yang, D. Olson, and C. Sheu. 2014. The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective. *Decision Support Systems* 59:119-126.

Chan, D. Y., and M. A. Vasarhelyi. 2011. Innovation and practice of continuous auditing. *International Journal of Accounting Information Systems* 12 (2):152-160.

Chand, D., G. Hachey, J. Hunton, V. Owhoso, and S. Vasudevan. 2005. A balanced scorecard based framework for assessing the strategic impacts of ERP systems. *Computers in Industry* 56 (6):558-572.

Chaudhuri, S., U. Dayal, and V. Narasayya. 2011. An overview of business intelligence technology. *Communications of the ACM* 54 (8):88-98.

Chen, H., R. H. Chiang, and V. C. Storey. 2012. Business intelligence and analytics: From big data to big impact. *MIS quarterly* 36 (4).

Chiu, T., and M. J. Jans. 2017. Process mining of event logs: a case study evaluating internal control effectiveness. *Available at SSRN 3136043*.

Christensen, C. 1997. *The innovator's dilemma: when new technologies cause great firms to fail*: Harvard Business Review Press.

Christensen, C., and M. Raynor. 2003. *The innovator's solution: Creating and sustaining successful growth*: Harvard Business Review Press.

Christensen, C. M. 2006. The ongoing process of building a theory of disruption. *Journal of Product Innovation Management* 23 (1):39-55.

Christensen, C. M., M. B. Horn, L. Caldera, and L. Soares. 2011. Disrupting College: How Disruptive Innovation Can Deliver Quality and Affordability to Postsecondary Education. *Innosight Institute*.

Christensen, C. M., M. E. Raynor, and R. McDonald. 2015. What is disruptive innovation. *Harvard business review* 93 (12):44-53.

Chugh, R., and S. Grandhi. 2013. Why Business Intelligence?: Significance of Business Intelligence Tools and Integrating BI Governance with Corporate Governance. *International Journal of E-Entrepreneurship and Innovation (IJEEI)* 4 (2):1-14.

CICA/AICPA. 1999. Continuous auditing. Research report, Toronto, Canada: The Canadian Institute of Chartered Accountants.

Cokins, G. 2013. Top 7 trends in management accounting. *Strategic Finance* 95 (6):21-30.

Cormode, G., and D. Srivastava. 2009. Anonymized data: generation, models, usage. Paper read at Proceedings of the 2009 ACM SIGMOD International Conference on Management of data, 2009.

Cosic, R., G. Shanks, and S. Maynard. 2012. Towards a business analytics capability maturity model. Paper read at ACIS 2012: Location, Location, Location: Proceedings of the 23rd Australasian Conference on Information Systems 2012, 2012.

Curtis, M. B., and E. A. Payne. 2008. An examination of contextual factors and individual characteristics affecting technology implementation decisions in auditing. *International Journal of Accounting Information Systems* 9 (2):104-121.

Cushing, B. E. 1977. On the possibility of optimal accounting principles. *Accounting Review*:308-321.

Dai, J., and M. A. Vasarhelyi. 2016. Imagineering Audit 4.0. *Journal of emerging technologies in Accounting* 13 (1):1-15.

———. 2017. Toward blockchain-based accounting and assurance. *Journal of Information Systems* 31 (3):5-21.

Danneels, E. 2004. Disruptive technology reconsidered: A critique and research agenda. *Journal of Product Innovation Management* 21 (4):246-258.

Davenport, T. 2014. *Big data at work: dispelling the myths, uncovering the opportunities*: Harvard Business Review Press.

Davenport, T. H. 2006. Competing on analytics. *Harvard business review* 84 (1):98.

Davenport, T. H., and J. G. Harris. 2007. *Competing on analytics: The new science of winning*: Harvard Business Press.

Davenport, T. H., J. G. Harris, and R. Morison. 2010. *Analytics at work: Smarter decisions, better results*: Harvard Business Press.

Davis, G. B. 1968. Auditing & EDp.

Davis, S., and T. Albright. 2004. An investigation of the effect of balanced scorecard implementation on financial performance. *Management accounting research* 15 (2):135-153.

Dechow, N., and J. Mouritsen. 2005. Enterprise resource planning systems, management control and the quest for integration. *Accounting, Organizations and Society* 30 (7):691-733.

DeLone, W. H., and E. R. McLean. 1992. Information systems success: The quest for the dependent variable. *Information Systems Research* 3 (1):60-95.

———. 2003. The DeLone and McLean model of information systems success: a ten-year update. *Journal of Management Information Systems* 19 (4):9-30.

Dhillon, I. S., and D. S. Modha. 2001. Concept decompositions for large sparse text data using clustering, 143-175.

Dilla, W., D. J. Janvrin, and R. Raschke. 2010. Interactive data visualization: New directions for accounting information systems research. *Journal of Information Systems* 24 (2):1-37.

Dilla, W. N., and R. L. Raschke. 2015. Data visualization for fraud detection: Practice implications and a call for future research. *International Journal of Accounting Information Systems* 16:1-22.

Ding, Y., X. Song, and Y. Zen. 2008. Forecasting financial condition of Chinese listed companies based on support vector machine. *Expert Systems with Applications* 34 (4):3081-3089.

Dowling, C., and S. Leech. 2007. Audit support systems and decision aids: Current practice and opportunities for future research. *International Journal of Accounting Information Systems* 8 (2):92-116.

Duman, E., and M. H. Ozcelik. 2011. Detecting credit card fraud by genetic algorithm and scatter search. *Expert Systems with Applications* 38 (10):13057-13063.

Dyson, R. A. 2015. Case studies in the new revenue recognition guidance. *The CPA Journal* 85 (3):22.

Edwards, J. B. 2001. ERP, Balanced Scorecard, and IT: How do they fit together? *Journal of Corporate Accounting & Finance* 12 (5):3-12.

Elliott, R. K. 2002. Twenty-first century assurance. *Auditing: A Journal of Practice & Theory* 21 (1):139-146.

FASB, F. A. S. B. 2016. Accounting Standards Codification Topic 606. Revenue from Contracts with Customers. Availabnle at: https://asc.fasb.org/imageRoot/32/79982032.pdf.

Fink, L., N. Yogev, and A. Even. 2016. Business Intelligence and Organizational Learning: An Empirical Investigation of Value Creation Processes. *Information & Management*.

Fischer, M. J. 1996. "Real-izing" the benefits of new technologies as a source of audit evidence: An interpretive field study. *Accounting, Organizations and Society* 21 (2-3):219-242.

Fisher, I. E., M. R. Garnsey, and M. E. Hughes. 2016. Natural language processing in accounting, auditing and finance: A synthesis of the literature with a roadmap for future research. *Intelligent Systems in Accounting, Finance and Management* 23 (3):157-214.

Forslund, H., and P. Jonsson. 2007. The impact of forecast information quality on supply chain performance. *International Journal of Operations & Production Management* 27 (1):90-107.

Foster, D. P., and R. A. Stine. 2004. Variable selection in data mining: Building a predictive model for bankruptcy. *Journal of the American Statistical Association* 99 (466):303-313.

Goel, S., J. Gangolly, S. R. Faerman, and O. Uzuner. 2010. Can linguistic predictors detect fraudulent financial filings? *Journal of emerging technologies in Accounting* 7 (1):25-46.

Goldman, S. M. 2009. BULLETIN NO. 09-06, edited by D. o. B. a. I. o. N. Jersey. https://www.state.nj.us/dobi//bulletins/blt09_06.pdf.

Gomaa, W. H., and A. A. Fahmy. 2013. A survey of text similarity approaches. *International Journal of Computer Applications* 68 (13):13-18.

Gonzalez, G. C., P. N. Sharma, and D. Galletta. 2012. Factors influencing the planned adoption of continuous monitoring technology. *Journal of Information Systems* 26 (2):53-69.

Goode, S., and D. Lacey. 2011. Detecting complex account fraud in the enterprise: The role of technical and non-technical controls. *Decision Support Systems* 50 (4):702-714.

Gorla, N., T. M. Somers, and B. Wong. 2010. Organizational impact of system quality, information quality, and service quality. *The Journal of Strategic Information Systems* 19 (3):207-228.

Grabski, S., S. Leech, and A. Sangster. 2009. *Management accounting in enterprise resource planning systems*: Butterworth-Heinemann.

Granlund, M., and T. Malmi. 2002. Moderate impact of ERPS on management accounting: a lag or permanent outcome? *Management accounting research* 13 (3):299-321.

Griffin, P. A., and A. M. Wright. 2015. Commentaries on Big Data's importance for accounting and auditing. *Accounting Horizons* 29 (2):377-379.

Gupta, V., and G. S. Lehal. 2010. A survey of text summarization extractive techniques. *Journal of emerging technologies in web intelligence* 2 (3):258-268.

Guttentag, D. 2015. Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current issues in Tourism* 18 (12):1192-1217.

Haug, A., and J. Stentoft Arlbjørn. 2011. Barriers to master data quality. *Journal of Enterprise Information Management* 24 (3):288-303.

Hogan, K. M. 2000. A multi-criteria model for predicting corporate bankruptcy using the analytical hierarchy process. *Applications of Management Science* 10:85.

Holsapple, C., A. Lee-Post, and R. Pakath. 2014. A unified foundation for business analytics. *Decision Support Systems* 64:130-141.

Holthausen, R. W., D. F. Larcker, and R. G. Sloan. 1995. Business unit innovation and the structure of executive compensation. *Journal of Accounting and Economics* 19 (2):279-313.

Holton, C. 2009. Identifying disgruntled employee systems fraud risk through text mining: A simple solution for a multi-billion dollar problem. *Decision Support Systems* 46:853-864.

Hua, Z., Y. Wang, X. Xu, B. Zhang, and L. Liang. 2007. Predicting corporate financial distress based on integration of support vector machine and logistic regression. *Expert Systems with Applications* 33 (2):434-440.

Huang, A. 2008. Similarity measures for text document clustering. Paper read at Proceedings of the sixth new zealand computer science research student conference (NZCSRSC2008), Christchurch, New Zealand, 2008.

Huang, F. 2019. Three essays on emerging technologies in accounting, Rutgers University-Graduate School-Newark.

Humpherys, S. L., K. C. Moffitt, M. B. Burns, J. K. Burgoon, and W. F. Felix. 2011. Identification of fraudulent financial statements using linguistic credibility analysis. *Decision Support Systems* 50:585-594.

Hwang, J., and C. M. Christensen. 2008. Disruptive innovation in health care delivery: a framework for business-model innovation. *Health Affairs* 27 (5):1329-1335.

IBM. 2012. The Four V's of Big Data. *Available at:* http://www.ibmbigdatahub.com/infographic/four-vs-big-data.

———. 2013. Descriptive, predictive, prescriptive: Transforming asset and facilities management with analytics. *Thought Leadership White Paper, October 2013*.

IEEE. 2017. IEEE Guide for Terms and Concepts in Intelligent Process Automation. In *IEEE Std 2755-2017*, 1-16.

Issa, H. 2013. Exceptional exceptions, Rutgers University-Graduate School-Newark.

Issa, H., and A. Kogan. 2014. A predictive ordered logistic regression model as a tool for quality review of control risk assessments. *Journal of Information Systems* 28 (2):209-229.

Issa, H., T. Sun, and M. A. Vasarhelyi. 2016. Research Ideas for Artificial Intelligence in Auditing: The Formalization of Audit and Workforce Supplementation. *Journal of emerging technologies in Accounting* 13 (2):1-20.

Ittner, C. D., and D. F. Larcker. 2001. Assessing empirical research in managerial accounting: a value-based management perspective. *Journal of Accounting and Economics* 32 (1):349-410.

Jans, M., M. Alles, and M. Vasarhelyi. 2013. The case for process mining in auditing: Sources of value added and areas of application. *International Journal of Accounting Information Systems* 14 (1):1-20.

Jans, M., M. G. Alles, and M. A. Vasarhelyi. 2014. A field study on the use of process mining of event logs as an analytical procedure in auditing. *The Accounting Review* 89 (5):1751-1773.

Janvrin, D., J. Bierstaker, and D. J. Lowe. 2008a. An examination of audit information technology use and perceived importance. *Accounting Horizons* 22 (1):1-21.

Janvrin, D., D. J. Lowe, and J. Bierstaker. 2008b. Auditor acceptance of computer-assisted audit techniques. *Iowa State University, Arizona State University and Villanova University* 4.

Jensen, J. R., and K. Lulla. 1987. Introductory digital image processing: a remote sensing perspective.

Kallunki, J.-P., E. K. Laitinen, and H. Silvola. 2011. Impact of enterprise resource planning systems on management control systems and firm performance. *International Journal of Accounting Information Systems* 12 (1):20-39.

Kanya, N., and S. Geetha. 2007. Information Extraction-a text mining approach.

Kaplan, R. S. 2008. Conceptual foundations of the balanced scorecard. *Handbooks of management accounting research* 3:1253-1269.

Kaplan, R. S., and D. P. Norton. 1992. The balanced scorecard: measures that drive performance. *Harvard business review* 70 (1):71-79.

———. 2001. Transforming the balanced scorecard from performance measurement to strategic management: Part I. *Accounting Horizons* 15 (1):87-104.

Keysers, D., T. Deselaers, H. A. Rowley, L.-L. Wang, and V. Carbune. 2017. Multi-Language Online Handwriting Recognition. *IEEE Trans. Pattern Anal. Mach. Intell.* 39 (6):1180-1194.

Kirkos, E., C. Spathis, and Y. Manolopoulos. 2007. Data mining techniques for the detection of fraudulent financial statements. *Expert Systems with Applications* 32 (4):995-1003.

Kogan, A., E. F. Sudit, and M. A. Vasarhelyi. 1999. Continuous online auditing: A program of research. *Journal of Information Systems* 13 (2):87-103.

Kohavi, R., L. Mason, R. Parekh, and Z. Zheng. 2004. Lessons and challenges from mining retail e-commerce data. *Machine Learning* 57 (1-2):83-113.

Koskivaara, E. 2004. Artificial neural networks in analytical review procedures. *Managerial Auditing Journal* 19 (2):191-223.

Krotov, V., and I. Junglas. 2008. RFID as a disruptive innovation. *Journal of theoretical and applied electronic commerce research* 3 (2):44-59.

Kwon, O., N. Lee, and B. Shin. 2014. Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management* 34 (3):387-394.

Lacity, M., L. P. Willcocks, and A. Craig. 2015. Robotic process automation at Telefonica O2.

Laney, D. 2001. 3D data management: Controlling data volume, velocity and variety. *META Group Research Note* 6:70.

Lee, S., and H.-j. Kim. 2008. News keyword extraction for topic tracking. Paper read at Networked Computing and Advanced Information Management, 2008. NCM'08. Fourth International Conference on.

Li, F. 2010. The information content of forward-looking statements in corporate filings—A naïve Bayesian machine learning approach. *Journal of Accounting Research* 48 (5):1049-1102.

Lin, W. T. 1979. Applications of goal programming in accounting. *Journal of Business Finance & Accounting* 6 (4):559-577.

Liu, Q. 2014. The application of exploratory data analysis in auditing, Rutgers University-Graduate School-Newark.

Liu, Q., and M. A. Vasarhelyi. 2014. Big questions in AIS research: Measurement, information processing, data analysis, and reporting. *Journal of Information Systems* 28 (1):1-17.

Liu, Q., L. Zhang, and H. Lee. 2019. Visual Audit Exploratory Data Analysis: Framework and Demonstration. *Working Paper, Rutgers University*.

Loraas, T., and C. J. Wolfe. 2006. Why wait? Modeling factors that influence the decision of when to learn a new use of technology. *Journal of Information Systems* 20 (2):1-23.

Lurie, N. H., and C. H. Mason. 2007. Visual representation: Implications for decision making. *Journal of marketing* 71 (1):160-177.

Manson, S., S. McCartney, and M. Sherer. 1997. Audit automation: Improving quality or keeping up appearances? *Current issues in auditing.—3 rd ed.—London: Paul Chapman Publishing Ltd*.

Marston, S., Z. Li, S. Bandyopadhyay, J. Zhang, and A. Ghalsasi. 2011. Cloud computing—The business perspective. *Decision Support Systems* 51 (1):176-189.

McCallum, A., and K. Nigam. 1998. A comparison of event models for naive bayes text classification. Paper read at AAAI-98 workshop on learning for text categorization.

Messier Jr, W. F., S. J. Kachelmeier, and K. L. Jensen. 2001. An experimental assessment of recent professional developments in nonstatistical audit sampling guidance. *Auditing: A Journal of Practice & Theory* 20 (1):81-96.

Moffitt, K. C., A. M. Rozario, and M. A. Vasarhelyi. 2018. Robotic process automation for auditing. *Journal of emerging technologies in Accounting* 15 (1):1-10.

Moffitt, K. C., and M. A. Vasarhelyi. 2013. AIS in an age of Big Data. *Journal of Information Systems* 27 (2):1-19.

Mori, S., H. Nishida, and H. Yamada. 1999. *Optical character recognition*: John Wiley & Sons, Inc.

Namburu, S. M., H. Tu, J. Luo, and K. R. Pattipati. 2005. Experiments on supervised learning algorithms for text categorization. Paper read at Aerospace Conference, 2005 IEEE, 2005.

Ngai, E. W., Y. Hu, Y. H. Wong, Y. Chen, and X. Sun. 2011. The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. *Decision Support Systems* 50 (3):559-569.

Nielsen, E. H., E. H. Nielsen, A. Jacobsen, and L. B. Pedersen. 2014. Management Accounting and Business Analytics. *Danish Journal of Management and Business* 78 (3-4):31-44.

Nielsen, S. 2015. The Impact of Business Analytics on Management Accounting. *Available at SSRN 2616363*.

No, W. G., K. Lee, F. Huang, and Q. Li. 2019. Multidimensional Audit Data Selection (MADS): A Framework for Using Data Analytics in the Audit Data Selection Process. *Working Paper, Rutgers University*.

Oracle. 2015. Big Data Analytics with Oracle Advanced Analytics. *Oracle White Paper/July 2015*.

Pang-Ning, T., M. Steinbach, and V. Kumar. 2006. *Introduction to data mining*. Conference Proceedings vols. Vol. 74.

Payne, E., and M. B. Curtis. 2008. Can the unified theory of acceptance and use of technology help us understand the adoption of computer-aided audit techniques by auditors. Paper read at Working Paper.

PCAOB, P. C. A. O. B. 2004. Auditing Standard No. 3 Audit Documentation. Available at: https://pcaobus.org/Rulemaking/Docket012/2004-06-09_Release_2004-006.pdf.

———. 2007. Auditing Standard No. 5 An Audit of Internal Control Over Financial Reporting That Is Integrated with An Audit of Financial Statements. Available at: https://pcaobus.org/Standards/Auditing/Pages/Auditing_Standard_5.aspx.

———. 2010a. Auditing Standard No. 9 Audit Planning. Available at https://pcaobus.org/Standards/Auditing/Pages/Auditing_Standard_9.aspx.

———. 2010b. Auditing Standard No. 11 Consideration of Materiality in Planning and Performing an Audit. Available at: https://pcaobus.org/Rulemaking/Docket%20026/Release_2010-004_Risk_Assessment.pdf.

———. 2010c. Auditing Standard No. 12 Identifying and Assessing Risks of Material Misstatement. Available at: https://pcaobus.org/Rulemaking/Docket%20026/Release_2010-004_Risk_Assessment.pdf.

———. 2010d. Auditing Standard No. 14 Evaluating Audit Results Available at: https://pcaobus.org/Rulemaking/Docket%20026/Release_2010-004_Risk_Assessment.pdf

———. 2010e. Auditing Standard No. 15 Audit Evidence. Available at: https://pcaobus.org/Standards/Auditing/Pages/Auditing_Standard_15.aspx.

———. 2014. Auditing Standard No. 18 Related Parties. Available at: https://pcaobus.org/Rulemaking/Docket038/Release_2014_002_Related_Parties.pdf.

———. 2015. Auditing Standard (AS) 1001: Responsibilities and Functions of the Independent Auditor. Available at: https://pcaobus.org/Standards/Auditing/Pages/AS1001.aspx.

———. 2017. Technology and the Audit of Today and Tomorrow. Available at: https://pcaobus.org/News/Speech/Pages/Harris-statement-PCAOB-AAA-4-20-17.aspx.

Perols, J. 2011. Financial statement fraud detection: An analysis of statistical and machine learning algorithms. *Auditing: A Journal of Practice & Theory* 30 (2):19-50.

Peters, M. D., B. Wieder, S. G. Sutton, and J. Wakefield. 2016. Business intelligence systems use in performance measurement capabilities: Implications for enhanced competitive advantage. *International Journal of Accounting Information Systems* 21:1-17.

Powell, T. C., and A. Dent-Micallef. 1997. Information technology as competitive advantage: The role of human, business, and technology resources. *Strategic management journal* 18 (5):375-405.

PricewaterhouseCoopers. 2016. Clarity from Above. Available at: http://www.pwc.pl/en/publikacje/2016/clarity-from-above.html.

Rau, L. F. 1991. Extracting company names from text. Paper read at Artificial Intelligence Applications, 1991. Proceedings., Seventh IEEE Conference on.

Redman, T. C. 1996. Improve data quality for competitive advantage. *QUALITY CONTROL AND APPLIED STATISTICS* 41:49-52.

Redman, T. C. 2008. *Data driven: profiting from your most important business asset*: Harvard Business Press.

Rozairo, A. M., and M. A. Vasarhely. 2018. Auditing with smart contracts.

Salton, G., and C.-S. Yang. 1973. On the specification of term values in automatic indexing. *Journal of documentation* 29 (4):351-372.

Sangster, A., S. A. Leech, and S. Grabski. 2009. ERP implementations and their impact upon management accountants. *JISTEM-Journal of Information Systems and Technology Management* 6 (2):125-142.

Scapens, R. W., and M. Jazayeri. 2003. ERP systems and management accounting change: opportunities or impacts? A research note. *European accounting review* 12 (1):201-233.

Schneider, G. P., J. Dai, D. J. Janvrin, K. Ajayi, and R. L. Raschke. 2015. Infer, predict, and assure: Accounting opportunities in data analytics. *Accounting Horizons* 29 (3):719-742.

Silvi, R., K. Moeller, and M. Schlaefke. 2010. Performance management analytics-the next extension in managerial accounting. *Available at SSRN 1656486*.

Smith, R. 2007. An overview of the Tesseract OCR engine. Paper read at Document Analysis and Recognition, 2007. ICDAR 2007. Ninth International Conference on.

Stewart, T. 2015. Data analytics for financial-statement Audits, Chapter 5 in AICPA, Audit Analytics and Continuous Audit: Looking Toward the Future. *American Institute Of Certified Public Accountants*.

Sutton, S. G., M. Holt, and V. Arnold. 2016. "The reports of my death are greatly exaggerated"—Artificial intelligence research in accounting. *International Journal of Accounting Information Systems* 22:60-73.

Taleizadeh, A. A., M. Noori-daryan, and L. E. Cárdenas-Barrón. 2015. Joint optimization of price, replenishment frequency, replenishment cycle and production rate in vendor managed inventory system with deteriorating items. *International Journal of Production Economics* 159:285-295.

Tan, C. E., C. A. Jubb, and K. A. Houghton. 1997. Auditor judgments: The effects of the partner's views on decision outcomes and cognitive effort. *Behavioral Research in Accounting* 9:157-175.

Tata, S., and J. M. Patel. 2007. Estimating the selectivity of tf-idf based cosine similarity predicates. *ACM Sigmod Record* 36 (2):7-12.

Teeter, R., and M. Vasarhelyi. 2015. Audit Analytics and Continuous Audit: Looking Toward the Future. *New York, NY: AICPA*.

Teitlebaum, A., and C. Robinson. 1975. The real risks in audit sampling. *Journal of Accounting Research*:70-91.

Thiprungsri, S., and M. A. Vasarhelyi. 2011. Cluster analysis for anomaly detection in accounting data: An audit approach.

Tom, M., V. L. Bart, and S. Xiaoyan. 2010. Exploring the feasibility and accuracy of Latent Semantic Analysis based text mining techniques to detect similarity between patent documents and scientific publications. *Scientometrics* 82 (2):289-306.

Tuarob, S., and C. S. Tucker. 2013. Fad or here to stay: Predicting product market adoption and longevity using large scale, social media data. Paper read at ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 2013.

Turner, D. M. 2016. What is Venture Management? http://www.ventureskies.com/blog/what-is-venture-management *retrieved 30 October 2016*.

Van der Aalst, W., T. Weijters, and L. Maruster. 2004. Workflow mining: Discovering process models from event logs. *IEEE Transactions on Knowledge and Data Engineering* 16 (9):1128-1142.

Van Der Meulen, R. 2016. Gartner survey reveals investment in big data is up but fewer organizations plan to invest. *Gartner Newsroom*.

Vasarhelyi, M. A., M. Alles, S. Kuenkaikaew, and J. Littley. 2012. The acceptance and adoption of continuous auditing by internal auditors: A micro analysis. *International Journal of Accounting Information Systems* 13 (3):267-281.

Vasarhelyi, M. A., M. G. Alles, and A. Kogan. 2004. Principles of analytic monitoring for continuous assurance. *Journal of emerging technologies in Accounting* 1 (1):1-21.

Vasarhelyi, M. A., and F. B. Halper. 1991. The Continuous Audit of Online Systems. *Auditing: A Journal of Practice & Theory* 10 (1):110-125.

Vasarhelyi, M. A., A. Kogan, and B. M. Tuttle. 2015. Big Data in Accounting: An Overview. *Accounting Horizons* 29 (2):381-396.

Venkatesh, V., and F. D. Davis. 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science* 46 (2):186-204.

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis. 2003. User acceptance of information technology: Toward a unified view. *MIS quarterly*:425-478.

Venkatesh, V., J. Y. Thong, and X. Xu. 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly* 36 (1):157-178.

Wang, S. 2010. A comprehensive survey of data mining-based accounting-fraud detection research. Paper read at 2010 International Conference on Intelligent Computation Technology and Automation.

Wang, Y., and A. Kogan. 2018. Designing confidentiality-preserving Blockchain-based transaction processing systems. *International Journal of Accounting Information Systems* 30:1-18.

Warren Jr, J. D., K. C. Moffitt, and P. Byrnes. 2015. How Big Data will change accounting. *Accounting Horizons* 29 (2):397-407.

Watson, H. J., and B. H. Wixom. 2007. The current state of business intelligence. *Computer* 40 (9):96-99.

Watts, S., G. Shankaranarayanan, and A. Even. 2009. Data quality assessment in context: A cognitive perspective. *Decision Support Systems* 48 (1):202-211.

Wu, X., X. Zhu, G.-Q. Wu, and W. Ding. 2014. Data mining with big data. *IEEE Transactions on Knowledge and Data Engineering* 26 (1):97-107.

Xu, H., J. Horn Nord, N. Brown, and G. Daryl Nord. 2002. Data quality issues in implementing an ERP. *Industrial Management & Data Systems* 102 (1):47-58.

Yancy, A. A. 2014. *The Balanced Scorecard and long-term financial performance: Evidence from publicly traded companies*: University of Southern California.

Yeoh, W., and A. Koronios. 2010. Critical success factors for business intelligence systems. *Journal of computer information systems* 50 (3):23-32.

Yeoh, W., and A. Popovič. 2016. Extending the understanding of critical success factors for implementing business intelligence systems. *Journal of the Association for Information Science and Technology* 67 (1):134-147.

Yoon, K., L. Hoogduin, and L. Zhang. 2015. Big Data as Complementary Audit Evidence. *Accounting Horizons* 29 (2):431-438.

Yu, D., and C. C. Hang. 2010. A reflective review of disruptive innovation theory. *International journal of management reviews* 12 (4):435-452.

Zhang, G., M. Y. Hu, B. E. Patuwo, and D. C. Indro. 1999. Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research* 116 (1):16-32.

Zhang, J., X. Yang, and D. Appelbaum. 2015. Toward effective Big Data analysis in continuous auditing. *Accounting Horizons* 29 (2):469-476.

Zhao, Y., and G. Karypis. 2002. Evaluation of hierarchical clustering algorithms for document datasets. Paper read at Proceedings of the eleventh international conference on Information and knowledge management, 2002.