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Behavioral Implications of Big Data's Impact on Audit Judgment and Decision Making and Future Research Directions

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SYNOPSIS: This paper addresses information processing weaknesses and limitations that can impede the effective use and analysis of Big Data in an audit environment. Drawing on the literature from psychology and auditing, we present the behavioral implications Big Data has on audit judgment by addressing the issues of information overload, information relevance, pattern recognition, and ambiguity. We also discuss the challenges that auditors encounter when incorporating Big Data in audit analyses and the various analytical tools that are currently used by companies in the analysis of Big Data. The manuscript concludes by raising questions that future research might address related to utilizing Big Data in auditing.

Keywords: Big Data; audit judgment; data analytics; information processing weaknesses.

INTRODUCTION

Data are continuously collected at an exponentially increasing rate, aided by the existence of various information systems and the decreasing cost of storage. The collection of such large amounts of data has been termed "Big Data," which is commonly referred to as a large population of datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze (McKinsey 2011). Further, Gartner Research (2014) defines Big Data as "high-volume, high-velocity, and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making." Many organizations have utilized Big Data to make more appropriate and timelier decisions about

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their business, such as risk assessments (King 2013; Myers 2013) and marketing (Been 2013; Lorinc 2013; Stevens-Huffman 2013; Strong 2013; Shields 2013). While collection of Big Data is relatively easy, the same cannot be said about processing and extracting useful information from large amounts of data. This challenge is especially true with respect to audits of financial statements and controls over financial statements (Alles 2013; Titera 2013).

Technological innovations (e.g., electronic commerce, online transactions) have led to a significant increase in the volume and complexity of accounting transactions, making it more challenging for auditors to analyze transactions. While most individuals will concur that the ability to collect, manage, and analyze data more effectively has the potential to lead to better judgment and decision making, Big Data has the potential to dramatically change the way auditors make decisions (i.e., risk assessments) and collect audit evidence (Moffitt and Vasarhelyi 2013; Issa 2013; Kogan, Alles, Vasarhelyi, and Wu 2011; Vasarhelyi and Halper 1991). For instance, Gray and Debreceny (2013) suggest that data mining has the potential to enhance the efficiency and effectiveness of audit procedures.[1] Auditors can utilize data mining techniques to analyze external data (e.g., census data, social media, news articles) in their assessments of client business risk, fraud risk, internal controls, going concern, etc. Additionally, instead of sampling techniques, the use of data analytic techniques allows auditors to analyze all client transactions for the year for exceptions and outliers, as well as trends. However, despite the availability of advanced data analytic tools, these tools are rarely used, if at all, in financial statement audits (Alles 2014; Gray and Debreceny 2013) and there is limited consensus about the role Big Data will have in auditing (Alles 2013).

While auditing standards provide auditors with rules and guidelines, the audit process involves considerable judgment related to the type and amount of evidence collected. For example, auditing standards require audit evidence to be sufficient and appropriate(Public Company Accounting Oversight Board [PCAOB] 2010, AS No. 15). What constitutes sufficient and appropriate audit evidence is a decision based solely on the auditor's judgment. Thus, the challenge for the auditing profession will be how to derive value from Big Data and ensure that audit judgments and decisions are based on quality information that is relevant and trustworthy. Therefore, it is important to gain an understanding of behavioral processes that auditors engage in to process information to make decisions and the impact of these behavioral processes in the Big Data environment. To help focus future research, this manuscript identifies information processing weaknesses and limitations that can impede the effective use and analysis of Big Data in an audit environment.

Data analytic tools enable auditors to import nearly limitless amounts of data for analysis, which potentially exacerbates information processing limitations. For example, research in psychology demonstrates that decision makers have limited ability to process large amounts of information required for complex decision making (Kleinmuntz 1990; Iselin 1988). Thus, this manuscript will examine the cognitive limitations that auditors potentially encounter while using tools for analyzing Big Data and interpreting the output generated by data analytic tools. Specifically, data analytic tools can assist auditors with tasks requiring more subjective judgments, since this is an area that has the potential to maximize the use of Big Data in addressing information processing weaknesses and limitations (e.g., fraud risk assessments). The potential opportunities and challenges to formalize these more complex judgments will be discussed in terms of data analytic tools (i.e., expert systems, data mining, etc.), as well as directions for future research. Additionally, tools that are currently used in other domains will be examined in the context of Big Data and those that would be best suited for the auditing profession (e.g., expert systems like AudEx) will be discussed.

[1] Data mining is defined as employing a variety of techniques to search through large amounts of data to identify unknown patterns or relationships, extract decision rules, or construct predictive models (Gray and Debreceny 2013).

This manuscript does not attempt to discuss how Big Data should be synthesized into the audit process (see Alles [2013] for a discussion of the value and the hurdles related to audit adoption of Big Data), but rather we examine, in the context of literature drawn from psychology and auditing, the behavioral implications of the analysis and interpretation of Big Data in the audit environment and provide a discussion of possible tools, given current technology, that can be used to address some of the identified problems that auditors potentially face in the Big Data environment.

The remainder of this manuscript proceeds as follows. The next section provides a general overview of the meaning of Big Data, followed by a discussion of the behavioral implications of Big Data for auditors. The fourth section focuses on the challenges associated with auditing Big Data and discusses technology that can be used by auditors to synthesize Big Data into the audit process. The final section offers future research opportunities and concluding remarks.

BIG DATA IN THE AUDIT CONTEXT

With the advent of Big Data, the quantity and diversity of information has increased and as a result Big Data provides auditors with tremendous potential to improve the efficiency and effectiveness of an audit engagement. For example, the analysis of cash transactions to ensure compliance with money laundering regulations is an example of a high-risk area where auditors can use Big Data analysis to focus on suspicious transactions. In this scenario the general rule is that any payment exceeding a specified amount requires special approval. To avoid the need to go through the process of obtaining this approval, some users may resort to keeping the amount of the transaction just below the threshold, or dividing the amount into multiple transactions, a phenomenon known as "split payments." While such transactions may not violate any internal controls, frequent occurrences may necessitate further investigations to ensure the legitimacy of these transactions. This scenario illustrates that by uncovering patterns that would remain otherwise unknown, data analytics used to extract information from larger volumes of data can help auditors identify high-risk areas where they should focus their investigative efforts.[2] "Detection of Fraud and Quantification of Risks" is identified as one of the top five benefits of analyzing Big Data (Russom 2011).

Despite the advanced data analytic tools available to collect data, the use of Big Data in the audit process potentially poses significant problems related to auditor judgment and decision making in a number of ways. First, the use of Big Data involves extracting information for analysis from an extremely larger population of data from multiple nonfinancial sources that auditors are not accustomed to having to collect and analyze during the conduct of an audit. While traditional data analytic tools such as Computer Assisted Audit Techniques (CAATs) have been shown to be effective (Dowling and Leech 2007), they are essentially data extraction tools that allow auditors to perform data analysis using queries. Additionally, existing CAATs have limited advanced statistical techniques and they do not have the capability to import nonfinancial information such as social networks logs, company emails, newspaper articles, etc. Thus, with CAATs it is up to the auditor to identify anomalies based on auditor-defined parameters versus more advanced data analytics (e.g., clustering) that analyze larger data sets to identify patterns and anomalies, which the auditor then has to further investigate. Thus, it is an empirical question of how auditors process information using more advanced data analytic tools (i.e., data mining).

Second, as opposed to explaining causation, the use of Big Data limits analyses to correlations through looking for patterns that might help predict future occurrences (Cukier and Mayer-Schoenberger 2013). This focus is problematic because correlations simply identify anomalies that direct the auditor's attention to investigate their causes. Causation is a critical and necessary aspect

[2] See Alles (2013) who develops a framework for the role of Big Data in auditing for a more in-depth discussion.

of auditing and correlations alone do not provide sufficient and appropriate audit evidence. Further, auditors' judgments are vulnerable to various problems, such as difficulty recognizing patterns of evidence (Bedard and Biggs 1991a; Nelson 2009; O'Donnell and Perkins 2011). Finally, the nature of Big Data is unstructured (e.g., emails, company blogs), which potentially results in the difficulty of choosing relevant data (Costonis 2012; Davenport, Barth, and Bean 2012; Hall 2012; Hyle 2012; Ede 2013; Golia 2013). Auditors are generally accustomed to collecting financial data and using the data to identify relevant information and discard noise. However, they are unaccustomed to collecting and incorporating nonfinancial data from nontraditional sources such as emails and social networks. As a result, the distinction between relevant and irrelevant data becomes more challenging due to auditors' unfamiliarity with analyzing the unstructured data that constitutes Big Data. This is especially problematic for less experienced auditors who have been found to attend to irrelevant information when forming their judgments (e.g., Hackenbrack 1992; Hoffman and Patton 1997; Waller and Zimbelman 2003). Further, unstructured data may be viewed as ambiguous and information ambiguity has been found to result in incorrect (e.g., inaccurate identification of cause of errors, less conservative going-concern assessments) audit judgments (Nelson and Kinney 1997; Backof, Bamber, and Carpenter 2014; Luippold and Kida 2012). In the following section we draw on existing literature in auditing and psychology to address the behavioral implications related to the use of data analytics in the analysis and interpretation of Big Data on auditor judgment and decision making.

BEHAVIORAL IMPLICATIONS RELATED TO THE ANALYSIS AND INTERPRETATION OF BIG DATA

As discussed, the use of data analytics to analyze Big Data has the potential to improve auditor judgment and decision making; however, in order to fully utilize the benefits, information processing weaknesses and cognitive limitations potentially experienced when analyzing and interpreting Big Data must first be overcome. Auditors are trained to collect, organize, and analyze financial information, and thus can leverage their core skills to help make nonfinancial Big Data smaller and more structured. However, the traditional audit methods and tools (e.g., CAATs) may not always be suitable to effectively and efficiently analyze Big Data. Thus, the ability to fully utilize the benefits of Big Data lays in more advanced data analytics techniques (e.g., clustering, neural networks), which potentially improve audit effectiveness. Data analytic tools used to analyze Big Data give auditors the ability to incorporate and use both structured (e.g., general ledger or transaction data) and unstructured (e.g., email communications, Wi-Fi sensors, electronic tags, free-text fields in databases) data to identify potential transactional anomalies (e.g., unauthorized disbursements), patterns of behavior (e.g., split payments to bypass transaction limit), and trends (e.g., increased fraudulent transactions before a big holiday). For example, fraud risk assessment is a highly complex and subjective judgment that auditors are required to make on every audit. Traditional audit methods have not always been very effective in identifying fraud risks. For instance, the use of standard fraud risk checklists and standard planning programs is associated with less effective analysis of the fraud risks and identification of tests to detect fraud (Pincus 1989; Eining, Jones, and Loebbecke 1997; Asare and Wright 2004).

In contrast, technologically advanced tools (e.g., data mining) and data analytics (e.g., predictive modeling) have been found to be effective tools that can be utilized in analyzing and evaluating Big Data in the assessment of fraud risks (Humpherys, Moffitt, Burns, Burgoon, and Felix 2011; Bochkay and Levine 2013). For example, negative correlations between nonfinancial and financial measures of business performance could be indicative of manipulation of financial information. Nonetheless, even in the Big Data environment limitations exist that cannot be overcome with advanced tools alone. Decisions made based on information derived from Big Data still involve interpretation and judgment. For instance, although technological tools can identify patterns, it is the auditor who is needed to analyze and evaluate these patterns. While these tools can be used to streamline data and assist in making decisions, without the auditors organizing and appropriately applying the information uncovered, analysis would not be effective or efficient and audit quality would not be improved. Based on our review of the literature, the major limitations potentially related to processing information in a Big Data environment include: information overload, information relevance, pattern recognition, and ambiguity.

Information Overload

Information overload is simply receiving too much information (Eppler and Mengis 2004). Decision makers possess limited ability to process large amounts of information, and existing research on the ability of individuals to combine cues from multiple sources consistently demonstrates less than favorable outcomes (Benbasat and Taylor 1982; Iselin 1988; Kleinmuntz 1990). Specifically, accounting research examining the effects of information overload suggests that large volumes of accounting information potentially lead to suboptimal financial and auditing judgments (Ashton 1974; Driver and Mock 1975; Miller and Gordon 1975; Chewning and Harrell 1990; Stocks and Harrell 1995; Simnett 1996; Alles, Brennan, Kogan, and Vasarhelyi 2006; Alles, Kogan, and Vasarhelyi 2008).

While data analytic tools make it possible to extract large volumes of data, analysis and interpretation of results may be problematic for auditors because the output still produces an overwhelming amount of data (Issa and Kogan 2014). For example, sophisticated analytic and data mining software tools enable auditors to capture and combine vast amounts of information from multiple sources. However, for data mining to be an effective analytic tool, auditors must have a clear understanding of the data, quality of the data, data relevance, etc. in order to draw appropriate conclusions. Additionally, the output from data mining has to be interpreted and evaluated in the context of the specific audit assertions being tested. While auditors are accustomed to incorporating nonfinancial information into their analysis—i.e., strategic systems auditing (Peecher, Schwartz, and Solomon 2007; Zhao and Harding 2013), the nature of analysis of Big Data and the resulting output could still potentially result in reduced audit quality due to information overload. This excessive information can overload the decision-making process, making it less efficient and less effective, leading to improper decisions (Casey 1980; Malhotra 1982), complications in distinguishing the relevant information (Jacoby 1977), difficulties in recognizing correlation between details and the overall perspective (Schneider 1987), disregard for large amounts of information (Herbig and Kramer 1994; Sparrow 1999; Bawden 2001), and lengthier decision times (Jacoby 1984).

Despite the potential problems related to information overload, utilization of Big Data in audits is achievable. Chewning and Harrell (1990) suggest that a possible approach to Big Data is to equip the decision maker with a decision model suited for the particular decision, which would have the effect of mitigating information processing difficulties resulting from high levels of information loads. Decision models of this type have been successfully used in other industries. For instance, many insurance companies use risk management software to collectively analyze different business units with regard to evaluating risk and controls designed to reduce and control risk, and to assess the procedures needed to improve the control environment (Hyle 2006). Insurers have also developed predictive analytics utilizing Big Data for pricing (i.e., price based on risk), optimizing risk eligibility (Rose 2013; Vasudeva 2013; Wilkinson 2013), and identifying fraudulent claims (Liyakasa 2012; Hughes 2013). The medical field has effectively used data mining operations to discover new trends and associations that could improve diagnostic and treatment functions to drive better patient outcomes (Martin 2013). These are tools that may be applicable to the audit environment and can be adopted by auditors to enable them to better process the data output in order to more effectively identify red flags or outliers. Indeed, similar technologies are being developed to be used in auditing. Issa (2013) proposes a weighted rule-based system that first identifies exceptions (cases that violate one or more business rules), and then utilizes knowledge extracted from an expert panel of senior auditors to prioritize and rank the identified exceptions. The objective of that framework is to aid the auditors, not only in examining the complete population of transactions (identifying exceptions), but also in handling the large number of exceptions that are normally generated by such systems (prioritizing exceptions). Consequently, auditors can focus their efforts on the more problematic cases, thus increasing overall audit efficiency.

Information Relevance

Increased information load may make it difficult to accurately identify relevant cues and may result in decreased performance (O'Reilly 1980). Thus, one negative outcome of exposure to excessive information is the inability to disregard irrelevant information. Higher levels of irrelevant information have been shown to reduce the decision makers' ability to identify relevant information and thus reduce their overall decision-making performance (Hodge and Reid 1971; Well 1971; Streufert 1973). This phenomenon is widely known as the dilution effect. In other words, the presence of a significant amount of non-diagnostic information (noise) tends to distract decision makers and dilute or lower the quality of their judgment (Nisbett, Zukier, and Lemley 1981; Hackenbrack 1992; Hoffman and Patton 1997; Waller and Zimbelman 2003; Lombardi 2012). In the auditing context, the dilution effect is particularly problematic because auditors must choose from a vast array of available information which items are most relevant for their audit judgments (Blay 2005).

Clearly, research suggests that attention to irrelevant information has the potential to significantly limit the value that can be obtained from incorporating Big Data into the audit process. However, this is not a problem that is unique to auditors. Many businesses are overwhelmed by the quantity of information and as a result, because of the raw unstructured nature of the data, they do not know how to get value out of it. Thus, the challenge of determining and extracting relevant information has to be addressed. Audit firms will need to identify the types of information relevant to the objectives of the audit process, especially nonfinancial information, because the nonfinancial information generated by Big Data is largely ambiguous and voluminous, two characteristics that have been shown to negatively impact auditor judgments (e.g., Stocks and Harrell 1995; Simnett 1996; Nelson and Kinney 1997).

The auditing profession can look to the insurance industry for examples of using Big Data to analyze business processes. For example, insurers have utilized data analytic tools such as analytics and telematics technology (i.e., the blending of computers and wireless telecommunications technologies, such as GPS) (Rose 2012, 2013; Bernier 2013) to calculate customer risk profiles in real-time. Clearly in this case, insurers are focusing on the data most relevant to the risks car drivers pose to the insurance company (i.e., auto risk)—as opposed to information that proxy for auto risk (e.g., car type, marital status, gender, credit history). Insurers have also used pattern and link analyses (i.e., evaluation of relationship between objects such as people, organizations, transactions, etc.) to detect insurance fraud (Hughes 2013), which is particularly relevant in an audit context where fraud risk assessment is a major component of the risk assessment process that auditors are required to perform. Specifically related to the audit context, Lombardi (2012) mitigated incorporation of irrelevant information in the decision process by having less experienced auditors use an expert system (a heuristic-based form of link analysis utilizing decision rules based on expert knowledge using structured data) in making a fraud risk assessment.

Pattern Recognition

Big Data provides the decision maker with the ability to search for patterns in a large population of data that would otherwise be undetectable in samples or even smaller data sets (Alles 2013). In the audit environment, for instance, the audit risk assessment process generally involves recognizing patterns in the data (i.e., complex data anomalies and inconsistencies) that may suggest errors or fraud (Libby 1985; Bedard and Biggs 1991a; Coakley and Brown 1993). While the output generated from the analysis of Big Data is a major advantage, prior research has shown that auditors are not very adept at recognizing patterns in financial and nonfinancial data (Bedard and Biggs 1991a; Bierstaker, Bedard, and Biggs 1999; Asare, Trompeter, and Wright 2000), applying prior knowledge to the current judgment task, and weighting evidence appropriately (Nelson 2009). Most of the findings regarding pattern recognition relate to audit research on analytical procedures (Biggs and Wild 1985; Bedard and Biggs 1991a; O'Donnell and Perkins 2011). Generally findings indicate that auditors have difficulty accurately extrapolating more complex time-series data (Biggs and Wild 1985); they do not readily combine information into patterns in making judgments (Bedard and Biggs 1991a); and they tend to focus on the incorrect cause of an error (Asare et al. 2000). Further, auditors may be unable to identify underlying inconsistencies in financial data and may evaluate financial inconsistencies on an account-by-account basis, as opposed to evaluating combinations of inconsistencies (Bedard and Biggs 1991a; Bierstaker et al. 1999).

Recent trends in technology provide evidence that auditors can be trained to overcome difficulties with pattern recognition. O'Donnell and Perkins (2011) find that auditors who use a systems-thinking tool focus more on diagnostic patterns of fluctuations in accounts, and correctly assess misstatement risk at higher levels when presented with inconsistent fluctuations in an analytical procedures task. Additionally, Selby (2011) finds that financial auditors who have procedural knowledge of automated controls are better able to interpret risk patterns in automated-control evidence. Thus, these findings suggest that providing financial auditors with more contextual experience and training will improve their ability to accurately recognize patterns in data, and more importantly to correctly interpret them. Several data analytic tools are currently being used that potentially mitigate the difficulties auditors experience with pattern recognition. As an example, cluster analysis and association rules have been extensively used in marketing and in the insurance industry. Further, emerging research has proven the efficiency of cluster analysis in identifying patterns and anomalies (Thiprungsri and Vasarhelyi 2011). While these tools have not been widely utilized by auditors, opportunities to utilize these tools in the audit context have upside potential. For example, cluster analysis can be used in a large population of transactions to identify cases where a manager excessively authorizes over the limit payments.

Ambiguity

Another aspect of Big Data is the unstructured nature of the data (e.g., heterogeneous and variable) that comes in many formats (e.g., text, image, video). These characteristics potentially create ambiguity. Ambiguity may arise from variations in the amount and type of information available, as well as from differences in the source reliability and lack of causal knowledge of observed events (Einhorn and Hogarth 1986). While Big Data offers a tremendous opportunity to discern new correlations between data, it presents a number of implementation challenges. Two major issues exist with Big Data: the nature of unstructured data and the difficulty in choosing data (Costonis 2012; Davenport et al. 2012; Hall 2012; Hyle 2012; Ede 2013; Golia 2013). First, unstructured data—information presented as images, scanned documents, transcribed entries—complicates the need for data management and processing software (Warner 2013). Second, although the focus largely remains on technological issues, companies are only as effective as their ability to compile data that address a strategic question (Costonis 2013). For example, in spite of the benefit to be gained from strategically using Big Data, many insurance companies do not feel adequately prepared to handle the challenge (Josefowicz 2013).

This problem is even more challenging when individuals charged with using data analytics have a low tolerance for ambiguity. Ambiguity-intolerant individuals actively seek to reduce uncertainty by focusing on simple solutions to resolve apparent ambiguous situations. Other information is neglected once a solution is identified (Lowe and Reckers 1997). In contrast, individuals with a high tolerance for ambiguity do not experience stress when information is vague, incomplete, unstructured, unclear, etc. (Norton 1975). Thus, ambiguity-intolerant individuals are more likely to prematurely end the decision process as compared to ambiguity-tolerant individuals (MacDonald 1970). Based on the research on tolerance for ambiguity, it is clear that a major consideration in how Big Data will be utilized is dependent on the auditor's tolerance for ambiguity. It is likely that ambiguity-intolerant auditors will be uncomfortable with the unstructured nature of Big Data and as a result may avoid or downplay ambiguous information that could result in less than optimal judgments. Further, it may also lead to inefficient auditing if ambiguity-intolerant auditors ignore information cues that can lead to more effective risk assessments.

Data analytic tools are available that can help auditors overcome cognitive limitations associated with ambiguity. For example, healthcare firms often receive ambiguous patient information and yet from this data actionable information must be developed in order to improve patients' outcomes (Moore, Eyestone, and Coddington 2013). They have addressed this issue by designing predictive models (Schouten 2013). Predictive analytics identifies meaningful patterns of data to foresee unknown future events using the insights of Big Data. If predictive models were developed from pattern-oriented learning tools and applied in auditing, then a prioritized list of risks and opportunities could be supplied to auditors, hence potentially increasing efficiency and effectiveness (Schouten 2013; Issa 2013).

Use of predictive models in auditing can be applied to ambiguous and highly subjective judgments such as going concern, fraud, etc., to model relationships among various relevant factors. By extracting transaction and historical data, as well as external data, for example, auditors can capture relationships among numerous factors to assess the risk that an entity may not continue as a going concern. Advanced analytic approaches using predictive modeling, detecting patterns and anomalies, and applied machine learning have successfully addressed shortcomings of traditional rules-based systems (Schouten 2013).

CHALLENGES OF BIG DATA IN AUDITING

One advantage of Big Data is its increased readability by computers (Lohr 2012). This same advantage leads to one of the biggest challenges that auditors face when dealing with Big Data—its unstructured nature. Traditional analytical tools such as Microsoft Excel or Microsoft Access require structured data to perform effectively. The main objective was to derive intelligence by comparing data that was downloaded and then validated and transformed against benchmarks and models derived from structured data. The introduction of Big Data leads to a shift in the focus of data analysis toward recognizing patterns within large amounts of data (Setty and Bakhshi 2013). Fortunately, there exist other data analytics tools, such as cluster analysis and association rules, that can operate effectively and efficiently with this kind of data.

Another challenge raised by Big Data is information overload, as discussed previously. The numbers of identified exceptions and anomalies are expected to increase dramatically. As a result, Big Data will aggravate the problem that already exists with traditional data, where auditors are inundated with such identified exceptions. Alles et al. (2006), Alles et al. (2008), and Debreceny, Gray, Tham, Goh, and Tang (2003) emphasize that the exceptions identified by continuous auditing systems are presented to the auditors without any further processing. Consequently, the analysis and examination of these exceptions lie on the shoulders of the auditors, whose human limitations lead to decreased overall audit efficiency (Debreceny et al. 2003; Alles et al. 2006; Alles et al. 2008; Issa 2013). Developing prioritization methodologies and incorporating them in decision-support systems can greatly help alleviate the burden of processing information (Issa 2013).

A third and decisive challenge is the lack of the adequate training and required skills to analyze Big Data. Most companies have developed the skills that proved useful in dealing with traditional data, but have not done the same for the new phenomenon that is Big Data (Russom 2011). In fact, adequate training and skills play a critical role in adopting analytical tools. As the variety, format, and accessibility of information evolves, companies will have to adjust to the rising complexity of Big Data (Papagiannis 2012). The increased complexity translates to an increased cost for companies, as the volume of data drives the cost of technology upward and puts pressure on firms to hire more data scientists and invest in database software (Golia 2013; Inbar 2013; Mansfield 2013).

Another important factor will be the adoption of appropriate data analytics tools. In fact, deciding which tool to use will play an important role in the usefulness of Big Data. Using a survey of 325 respondents from data management professionals, Russom (2011) categorizes Big Data analytics into four major groups depending on their potential growth (of utilization) and organizational commitment, e.g., whether the popularity of the tool will increase or decrease, and the likelihood that the company will stick with the specific tool.[3] The first group is expected to increase in popularity (strong potential growth) and includes predictive models, machine learning techniques, artificial intelligence, statistical analytics, as well as visualization techniques. Examples of this group include real time analytics that analyze data to update dashboards used by management or auditors in order to identify problems in real-time. Also included in this group are text-mining tools, which are gaining popularity due to their applicability to a wide array of problems, such as risk assessments and fraud (Russom 2011).

The second group comprises data warehouses and dedicated database management systems (DBMS). Due to the increased availability of a variety of platforms, these analytics are likely to experience a higher adoption rate. Companies can select from a variety of products, many of which come packed with built-in analytics (or in-database analytics) that can facilitate the auditors' work of examining the data. The third group is relatively new and is not well known to auditors, despite its advantage of exploiting distributed computing. This capability is especially important with globalization, where captured data is scattered around the globe. Such tools (e.g., Hadoop Distributed File System) enable auditors to handle data of various types (e.g., text, financial) and from various sources (emails, ERPs). Finally, the last group consists of the tools that are currently in use by the majority of companies and that are expected to vanish in time due to their limited scalability, such as traditional database management systems (DBMS) that were designed for traditionally structured data (Russom 2011).

In summary, the technology necessary to utilize Big Data in audits is currently available and appears to be affordable. Other companies and industries have benefited from identifying partners and consultants with expertise in garnering Big Data solutions (Hamilton 2013). Audit firms could also initiate partnerships with Big Data solutions companies, such as Data Alliance Collaborative, to create analytical methods that cut costs while improving outcomes (Conn 2013). This partnering would save substantial time and costs by adopting an already functional tool that is being used successfully in other industries. Auditors could then focus more on making assessments and

[3] Potential growth refers to how much the use of a certain Big Data tool will increase/decrease in the future. It was calculated as the difference (for each tool) between the responses to Russom's survey with regard to the questions "Using today" and "Using in three years." Organizational commitments, on the other hand, refer to the percentage of the survey's respondents who are committed to utilizing a certain Big Data tool today, in three years, or both.

evaluations of the relevant information extracted from Big Data, as opposed to spending time developing and employing methods and tools to analyze the unstructured or structured data. For example, if a third-party consultant used data mining tools to extract relevant fraud cues from Big Data for audit firms, then auditors could then spend time focusing on assessing the level of fraud risk for each extracted cue. This approach would likely enhance fraud risk assessments, as only the relevant information from Big Data is being identified by a data analytics tool.

DISCUSSION

Future Research Directions

Table 1 provides a summary of suggested research questions. The list is not meant to be all inclusive, but rather it should be considered a starting point to spur future research on this very important topic of information processing weaknesses and limitations that can impede the effective use and analysis of Big Data in an audit environment.

The academic research community serves an important role in helping to advance our understanding of the effects, both positive and negative, of Big Data on auditor judgment. The knowledge that has been gained from existing judgment and decision-making audit research provides an important input into understanding the information processing heuristics that auditors may employ to simplify and reduce complex integrative information. The findings of prior research should also be considered in light of the many advances in technology and how this technology can be leveraged to improve auditor judgment and decision making.

Big Data clearly provides an opportunity to use powerful analytical tools and, thus it is important that audit firms find a way to capitalize on its value in order to enhance the audit process. Therefore, despite the behavioral limitations as they relate to auditor judgment and decision making, as identified in this manuscript, it is important to investigate solutions/approaches that may mitigate the negative impact on auditor judgment. For example, when confronted with information overload, decision makers revert to potentially biased heuristics to process the information (Benbasat and Taylor 1982). In this case individuals may resort to satisficing: focusing only on the information necessary to reach a satisfactory decision when they are unable to consider all information. Therefore, research is important on whether and how the effect of experience, identified in prior literature as mitigating many biased heuristics, reduces the negative effects of information overload. The findings from research in this area will allow training with regard to Big Data to be more customized.

Conclusion

Auditors face a complex challenge in collecting, analyzing, and synthesizing large amounts of data from multiple sources in order to form judgments. Indeed, difficulties in recognizing patterns suggestive of management fraud or going-concern issues, rather than ineffective auditing, are generally thought to be the cause of many audit failures (Lemon, Tatum, and Turley 2000). Therefore, it is extremely important that audit firms be prepared to address the problems that can arise from integrating Big Data into the audit process and ensure that audit judgments and decisions are based on quality information that is relevant and trustworthy. To help focus future research, this manuscript addresses the current state of Big Data with regard to the audit environment, discusses selected information processing weaknesses and limitations that can impede the effective use and analysis of Big Data, and identifies existing technology that can be leveraged in an audit environment.

Overall, behavioral implications related to information overload, irrelevant information, pattern recognition, and ambiguity potentially are major limitations that auditors will have to overcome in

TABLE 1

Summary of Major Research Findings and Questions for Future Research

Major Findings	**Selected Questions for Future Research**
Auditor Characteristics Skills	
1. Individuals tend to consider only the information that is explicitly represented in their mental models in decision making and more elaborate mental models facilitate acquisition and processing of information cues (Legrenzi, Girotto, and Johnson-Laird 1993; Legrenzi and Girotto 1996).	• What mental models are necessary to help auditors build knowledge structures that will allow them to more effectively process and evaluate more complex data? How can these knowledge structures be developed? • Similarly, how do auditors map unstructured information into risk assessments? Will this information even influence risk assessments?
2. Research demonstrates that domain and task experience accounts for different cognitive processes used by auditors (Libby and Tan 1994; Bedard and Biggs 1991b; Bonner and Lewis 1990).	• Is this effect evident in environments where there are significant amounts of data? • What are the effects of experience, if any? • Along the lines of experience, are less experienced auditors (i.e., the millennial generation) better prepared to integrate Big Data into their judgment process? In other words, are they more comfortable with information overload and ambiguity because they have grown up in the age of more advanced technology and they are big users of social media?
Information Processing	
3. In order to deal with too much information, a decision maker may stop searching once a satisfactory solution has been found; i.e., the satisficing heuristic (Buchanan and Kock 2001).	• What strategies do individuals use in analyzing and evaluating large quantities of information? Think-aloud verbal protocols can be employed to gather evidence about the auditors' reasoning and judgment process in the Big Data context. • What successful strategies can be leveraged from strategic systems auditing (i.e., top down approach) to assist auditors in the integration of Big Data in the audit process? As an example, Brazel and Agoglia (2007) find that consideration of both financial and nonfinancial performance measures result in an auditor's increased ability to predict fraudulent activities.
Training and Development	
4. Lombardi and Dull (2013) develop an expert system to help less experienced auditors filter out irrelevant information in a fraud-risk assessment task. Can a similar system be used to improve auditors' ability to more effectively recognize patterns or discount irrelevant information in large data sets?	• What are the types of training or decision aid interventions that can be utilized to mitigate inaccurate judgments? • How should the accounting curriculum be extended to provide future auditors with the necessary skills to deal with Big Data?

(continued on next page)

TABLE 1 (continued)

Major Findings	Selected Questions for Future Research
	• What skills should the audit engagement team now possess? Since audits are conducted by teams of auditors (both experienced and less experienced), the overall skill sets of the audit teams and roles of the members will likely need to change to fit the new mold to incorporate Big Data. For example, cross-functional and interdisciplinary audit teams (e.g., IT specialist, statisticians) may take on greater importance.
Technology 5. As audited financial statements are becoming more predictive in nature (i.e., fair value measurement) as opposed to just historical data, utilizing already available technologies (i.e., decision aids such as expert systems) from other industries, and adapting them to the audit industry may aid evaluating and assessing Big Data. Lombardi (2012) demonstrates that through the use of an expert system, adapted from the medical profession, less than optimal fraud risk assessments could be mitigated with Big Data.	• What predictive models currently used by other industries (i.e., insurance industry) are relevant for use by audit firms? • What analytical tools are applicable for auditors and more likely to be used by auditors? A study similar to the study conducted by Russom (2011), as well as a field study interviewing practitioners, could be initiated to gain a better understanding of practitioner needs and potential roadblocks to the use of technology such as predictive analytics to examine the analytical tools that prove applicable and more popular to auditors. Additionally, research can also examine auditors' adoption of such new analytical tools following various technology acceptance models (Davis 1985; Venkatesh and Davis 2000; Venkatesh, Morris, G. David, and F. David 2003). This direction may lead to additional research that would propose improved analytical tools specific to the auditing area. Such improved tools should support the evidence-collection requirements of the audit profession.

order to fully realize the value of Big Data. However, tools such as expert systems, predictive analytics, etc. are available to help mitigate these limitations and improve audit efficiency and effectiveness. For example, auditors now have the ability to greatly improve tests of controls by eliminating sampling of data and utilizing technology that rapidly retrieves data and allows for the examination of every instance of a particular type of transaction (Vorhies 2013). The potential of Big Data to enhance audit judgment and thus, audit quality, is significant. In order to achieve extensive implementation of Big Data in the auditing profession, new capabilities, new metrics, and new ways of thinking will be necessary.

This manuscript also suggests promising research directions. As noted earlier, academic research has examined the effectiveness of various data analytic tools in assessing fraud risk, transactional anomalies, etc., and the results of this research can provide important insight to the auditing profession regarding advanced technologies that auditors can leverage on audits. More academic research is necessary to fully comprehend the effects of moving away from more traditional audit processes to fully leverage the benefits of Big Data and how the use of more advanced data analytics will impact auditor judgment.

Overall, incorporating Big Data into the audit process is a value-added proposition for auditors, but this does not come without challenges. Auditors have to be mindful that without additional investigation, correlations generated from analyses of Big Data do not result in sufficient and appropriate audit evidence. Additional audit effort will be necessary to determine the causes of identified anomalies or suspicious transactions. Therefore, Big Data should not be used as the only source of evidence, but rather to corroborate audit findings and identify risks. With respect to data analytics, there are numerous advanced tools available to auditors. However, auditors must ensure that they select the optimal data analytic tool(s) and data source(s). Use of an inappropriate tool can result in, for example, significant Type II errors that would negatively impact audit quality (i.e., effectiveness), or Type I errors leading to unnecessary audit effort (i.e., efficiency). Further, it is very important that auditors consider the quality of the nonfinancial data that they incorporate in their analyses. Since there are no commonly accepted formalized audit data standards, auditing firms should either develop their own quality control standards, or adopt the data standards currently being promoted by the AICPA, regarding the use of Big Data.

REFERENCES

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

Alles, M. 2013. *Developing a Framework for the Role of Big Data in Auditing: A Synthesis of the Literature*. Working paper, Rutgers, The State University of New Jersey.

Alles, M. 2014. *Drivers of the Adoption and Facilitators of the Evolution of Big Data by the Audit Profession*. Working paper, Rutgers, The State University of New Jersey.

Asare, S., G. Trompeter, and A. Wright. 2000. The effect of accountability and time budgets on auditors' testing strategies judgments. *Contemporary Accounting Research* 17 (4): 539–560.

Asare, S. K., and A. M. Wright. 2004. The effectiveness of alternate risk assessment and program planning tools in a fraud setting. *Contemporary Accounting Research* 21 (2): 325–352.

Ashton, R. H. 1974. Behavioral implications of information overload in managerial accounting reports. *Cost and Management* 48 (4): 37–40.

Backof, A. G., M. E. Bamber, and T. Carpenter. 2014. Do auditor judgment frameworks help in constraining aggressive reporting: Evidence under more precise and less precise accounting standards. (May 17, 2014). *CAAA Annual Conference*. Available at: http:// http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1982041

Bawden, D. 2001. Information and digital literacies: A review of concepts. *Journal of Documentation* 57 (2): 218–259.

Bedard, J. C., and S. R. Biggs. 1991a. Pattern recognition, hypotheses generation, and auditor performance in an analytical task. *The Accounting Review* 66 (3): 622–642.

Bedard, J. C., and S. R. Biggs. 1991b. The effect of domain-specific experience on evaluation of management representations in analytical procedures. *Auditing: A Journal of Practice & Theory* (Supplement) 77–90.

Been, R. 2013. Data mining personalizes direct mail. *Automotive News* 87 (6583): 3–32.

Benbasat, I., and R. N. Taylor. 1982. Behavioral aspects of information processing for the design of management information systems. *IEEE Transactions On Systems, Man and Cybernetics* 12 (4): 439–450. Available at: http://cpe.njit.edu/dlnotes/CIS/CIS732_447/Cis732_4R.pdf

Bernier, P. 2013. Getting personal. *Customer (Technology Marketing Corporation)* 31 (7): 8.

Bierstaker, J. L., J. C. Bedard, and S. F. Biggs. 1999. The role of problem representation shifts in auditor decision processes in analytical procedures. *Auditing: A Journal of Practice & Theory* 18 (1): 18–36.

Biggs, S. F., and J. J. Wild. 1985. An investigation of auditor judgment in analytical review. *The Accounting Review*: 607–633.

Blay, A. D. 2005. Independence threats, litigation risk, and the auditor's decision process. *Contemporary Accounting Research* 22: 759–789.

Bochkay, K., and C. Levine. 2013. Using MD&A to improve earnings forecasts. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2253054

Bonner, S. E., and B. L. Lewis. 1990. Determinants of auditor expertise. *Journal of Accounting Research* 28 (Supplement): 1–20.

Brazel, J. F., and C. P. Agoglia. 2007. An examination of auditor planning judgments in a complex accounting information system environment. *Contemporary Accounting Research* 24 (4): 1059–1083.

Buchanan, J., and N. Kock. 2001. Information overload: A decision making perspective. In *Multiple Criteria Decision Making in the New Millennium*, 29–58. Berlin-Heidelberg, Germany: Springer.

Casey, C. J. Jr. 1980. Variation in accounting information load: The effect on loan officers' prediction of bankruptcy. *The Accounting Review* (January): 36–49.

Chewning, E. G. Jr., and A. M. Harrell. 1990. The effect of information load on decision makers' cue utilization levels and decision quality in a financial distress decision task. *Accounting, Organizations and Society* 527–542.

Coakley, J. R., and C. E. Brown. 1993. Artificial neural networks applied to ratio analysis in the analytical review process. *Intelligent Systems in Accounting, Finance and Management* 2 (1): 19–39.

Conn, J. 2013. Pairing up. *Modern Healthcare* 43 (24): 8–9.

Costonis, M. 2012. Big Data. *Best's Review* 113 (1): 80.

Costonis, M. 2013. Tackling Big Data. *Best's Review* (July): 93.

Cukier, K., and V. Mayer-Schoenberger. 2013. The rise of Big Data: How it's changing the way we think about the world. *Foreign Affairs* (May/June).

Davenport, T. H., P. Barth, and R. Bean. 2012. How Big Data is different. *MIT Sloan Management Review* 54 (1): 43–46.

Davis, F. D. 1985. *A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results*. Dissertation, Massachusetts Institute of Technology.

Debreceny, R., G. L. Gray, W. Tham, K. Goh, and P. Tang. 2003. The development of embedded audit modules to support continuous monitoring in the electronic commerce environment. (February): 169–185.

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.

Driver, M. J., and T. J. Mock. 1975. Human information processing, decision style theory, and accounting information systems. *The Accounting Review*: 490–508.

Ede, A. 2013. There's gold in them thar fans. *NZ Marketing Magazine* (November): 70–71.

Einhorn, H. J., and R. M. Hogarth. 1986. Judging probable cause. *Psychological Bulletin* 99 (1): 3–19.

Eining, M. M., D. R. Jones, and J. K. Loebbecke. 1997. Reliance on decision aids: An examination of auditors' assessment of management fraud. *Auditing: A Journal of Practice & Theory* 16 (2): 1–19.

Eppler, M. J., and J. Mengis. 2004. The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society* 20 (5): 325–344.

Gartner Research. 2014. *Gartner IT Glossary*. Available at: http://www.gartner.com/it-glossary/?s=big+data.

Golia, N. 2013. What Big Data means for infrastructure costs. *Insurance and Technology* (May): 30–31.

Gray, G. L., and R. S. Debreceny. 2013. *A Taxonomy to Guide Research on the Application of Data Mining to Fraud Detection in Financial Statement Audits*. Working paper, California State University, Northridge.

Hackenbrack, K. 1992. Implications of seemingly irrelevant evidence in audit judgment. *Journal of Accounting Research* 30 (1): 126–136.

Hall, K. 2012. Technology transforms how Aviva takes its insurance models to market. *Computer Weekly* (June): 8.

Hamilton, B. 2013. Impacts of Big Data. *Health Management Technology* (August): 12–13.

Harris, C. 2013. Diving into Big Data. *Canadian Underwriter* (February): 28–36.

Herbig, P. A., and H. Kramer. 1994. The effect of information overload on the innovation choice process: Innovation overload. *Journal of Consumer Marketing* 11 (2): 45–54.

Hodge, M. H., and L. S. Reid. 1971. The influence of similarity between relevant and irrelevant information upon a complex identification task. *Perception and Psychophysics* 10 (4): 193–196.

Hoffman, V. B., and J. M. Patton. 1997. Accountability, the dilution effect, and conservatism in auditors' fraud judgments. *Journal of Accounting Research* 35 (2): 227–237.

Hughes, P. 2013. Making waves. *Best's Review* 114 (4): 44.

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 (3): 585–594.

Hyle, R. R. 2006. *The Path to Success: Or the Road to Ruin? Techdecisions for Insurance*. Erlanger, KY: National Underwriter Company dba Summit Business Media.

Hyle, R. R. 2012. Blow up. *Tech Decisions for Insurance* 14 (3): 40–44.

Inbar, D. 2013. Making the most out of your data: Big Data opportunities. *Siliconindia* (February): 35.

Iselin, E. R. 1988. The effects of information load and information diversity on decision quality in a structured decision task. *Accounting, Organizations and Society:* 147–164.

Issa, H. 2013. *Exceptional Exceptions*. Dissertation, Rutgers, The State University of New Jersey.

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.

Jacoby, J. 1977. Information load and decision quality: Some contested issues. *Journal of Marketing Research:* 569–573.

Jacoby, J. 1984. Perspectives on information overload. *Journal of Consumer Research:* 432–435.

Josefowicz, M. 2013. 5 Issues driving insurer IT strategy in the next 5 years. *Insurance Networking News* 16 (1): 31. Available at: http://www.insurancenetworking.com/issues/2008_91/5-issues-driving-it-strategy-next-5-years-31882-1.html

King, W. B. 2013. How CUs can use Big Data to drive big revenue. *Credit Union Journal* 17 (37): 24.

Kleinmuntz, B. 1990. Why we still use our heads instead of formulas: Toward an integrative approach. *Psychological Bulletin* 107 (3): 296–310.

Kogan, A., M. G. Alles, M. A. Vasarhelyi, and J. Wu. 2011. *Analytical Procedures for Continuous Data Level Auditing: Continuity Equations*. Working paper, Rutgers, The State University of New Jersey, Newark.

Legrenzi, P., V. Girotto, and P. N. Johnson-Laird. 1993. Focusing in reasoning and decision making. *Cognition* 49 (1): 37–66.

Legrenzi, P., and V. Girotto. 1996. Mental models in reasoning and decision making processes. *Mental Models in Cognitive Science:* 95–118.

Lemon, W. M., K. W. Tatum, and W. S. Turley. 2000. *Developments in the Audit Methodologies of Large Accounting Firms*. London, U.K.: Auditing Practices Board.

Libby, R. 1985. Availability and the generation of hypotheses in analytical review. *Journal of Accounting Research:* 648–667.

Libby, R., and H. T. Tan. 1994. Modeling the determinants of audit expertise. *Accounting, Organizations and Society* 19 (November): 701–716.

Liyakasa, K. 2012. Big Data analytics can help improve information security. *CRM Magazine* 16 (1): 11.

Lohr, S. 2012. The age of Big Data. *New York Times* (Feb. 11). Available at: http://www.nytimes.com/2012/02/12/sunday-review/big-datas-impact-in-the-world.html?pagewanted=all&_r=0

Lombardi, D. R. 2012. *Using an Expert System to Debias Auditor Judgment: An Experimental Study*. Dissertation, Rutgers, The State University of New Jersey.

Lombardi, D. R., and R. Dull. 2013. *The Development of AudEx: An Audit Data Assessment System*. Working paper, Villanova University.

Lorinc, J. 2013. Big Data for small firms. *Profit* 32 (5): 9–10.

Lowe, D. J., and P. M. Reckers. 1997. The influence of outcome effects, decision aid usage, and intolerance of ambiguity on evaluations of professional audit judgement. *International Journal of Auditing* 1 (1): 43–58.

Luippold, B. L., and T. E. Kida. 2012. The impact of initial information ambiguity on the accuracy of analytical review judgments. *Auditing: A Journal of Practice & Theory* 31 (2): 113–129.

Malhotra, N. K. 1982. Information load and consumer decision making. *Journal of Consumer Research:* 419–430.

MacDonald, Jr., A. P. 1970. Revised scale for ambiguity tolerance: Reliability and validity. *Psychological Reports* 26 (3): 791–798.

Mansfield, D. 2013. Keepin' it clean. *NZ Marketing Magazine* (July): 72.

Martin, M. 2013. Big Data/social media combo poised to advance healthcare. *HPC Source* (April): 33–35.

McKinsey. 2011. *Big Data: The Next Frontier for Innovation, Competition, and Productivity*. McKinsey Global Institute (June). Available at: http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation

Miller, D., and L. A. Gordon. 1975. Conceptual levels and the design of accounting information systems. *Decision Sciences* 6 (2): 259–269.

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

Moore, K. D., K. Eyestone, and D. C. Coddington. 2013. The big deal about Big Data. *Healthcare Financial Management* (August): 61–68.

Myers, M. 2013. Credit screening and analysis tools extend to collections: Searching for peaches among unmarked cans. *Business Credit* 115 (8): 32–34.

Nelson, M. W., and W. R. Kinney, Jr. 1997. The effect of ambiguity on loss contingency reporting judgments. *The Accounting Review:* 257–274.

Nelson, M. W. 2009. A model and literature review of professional skepticism in auditing. *Auditing: A Journal of Practice & Theory* 28 (2): 1–34.

Nisbett, R. E., H. Zukier, and R. E. Lemley. 1981. Nondiagnostic information weakens the implications of diagnostic information. *Cognitive Psychology* 13 (1): 248–277.

Norton, R. 1975. Measurement of ambiguity tolerance. *Journal of Personality Assessment* 39: 607–619.

O' Donnell, E., and J. D. Perkins. 2011. Assessing risk with analytical procedures: Do systems-thinking tools help auditors focus on diagnostic patterns? *Auditing: A Journal of Practice & Theory* 30 (4): 273–282.

O'Reilly, C. A. 1980. Individuals and information overload in organizations: Is more necessarily better? *Academy of Management Journal* 23 (4): 684–696.

Papagiannis, S. 2012. Staying ahead of the data tsunami. *Canadian Underwriter* (November): 12–15.

Peecher, M. E., R. Schwartz, and I. Solomon. 2007. It's all about audit quality: Perspectives on strategic-systems auditing. *Accounting, Organizations and Society* 32 (4): 463–485.

Pincus, K. V. 1989. The efficacy of a red flags questionnaire for assessing the possibility of fraud. *Accounting, Organizations and Society* 14 (1): 153–163.

Public Company Accounting Oversight Board (PCAOB). 2010. *Audit Evidence*. Auditing Standard (AS) No. 15. Washington, DC: PCAOB.

Rose, S. 2012. Big Data under the microscope. *Canadian Underwriter* 79 (6): 20–23.

Rose, S. 2013. Start making sense. *Canadian Underwriter* 80 (3): 57–59.

Russom, P. 2011. Big Data analytics. *TDWI Best Practices Report* (Fourth Quarter).

Schneider, S. C. 1987. Information overload: Causes and consequences. *Human Systems Management* 7 (2): 143–153.

Schouten, P. 2013. Big Data in health care: Solving provider revenue leakage with advanced analytics. *Healthcare Financial Management* (February): 40–42.

Selby, D. 2011. Can financial statement auditors identify risk patterns in IT control evidence? *International Journal of Business, Humanities and Technology* 1 (3).

Setty, K., and R. Bakhshi. 2013. What is Big Data and what does it have to do with IT audit? *ISACA Journal*: 3.

Shields, M. 2013. Erin Matts. *Adweek* 54 (36): 10.

Simnett, R. 1996. The effect of information selection, information processing and task complexity on predictive accuracy of auditors. *Accounting, Organizations and Society* 21 (7): 699–719.

Sparrow, P. 1999. Strategy and cognition: Understanding the role of management knowledge structures, organizational memory, and information overload. *Creativity and Innovation Management* 8 (2): 140–148.

Stevens-Huffman, L. 2013. Profit from Big Data. *Smart Business St. Louis* 6 (11): 16–19.

Stocks, M. H., and A. Harrell. 1995. The impact of an increase in accounting information level on the judgment quality of individuals and groups. *Accounting, Organizations and Society* 20 (7): 685–700.

Streufert, S. C. 1973. Effects of information relevance on decision making in complex environments. *Memory and Cognition* 1 (3): 224–228.

Strong, C. 2013. When marketing met Big Data. *Market Leader* (Q4): 32–35.

Thiprungsri, S., and M. A. Vasarhelyi. 2011. Cluster analysis for anomaly detection in accounting data: An audit approach. *The International Journal of Digital Accounting Research* 11: 6.

Titera, W. R. 2013. Updating audit standard—Enabling audit data analysis. *Journal of Information Systems* 27 (1): 325–331. Available at: http://connection.ebscohost.com/c/articles/88181973/updating-audit-standard-enabling-audit-data-analysis

Vasarhelyi, M. A., and F. B. Halper. 1991. The continuous audit of online systems. *Auditing: A Journal of Practice & Theory* 10 (1): 110–125.

Vasudeva, V. 2013. Reinventing the wheel. *Best's Review* 114 (1): 26–28.

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.

Vorhies, B. 2013. *A Brief History of Big Data Technologies from SQL to NoSQL to Hadoop and Beyond*. Available at: http://www.data-magnum.com/a-brief-history-of-big-data-technologies-from-sql-to-nosql-to-hadoop-and-beyond

Waller, W. S., and M. F. Zimbelman. 2003. A cognitive footprint in archival data: Generalizing the dilution effect from laboratory to field settings. *Organizational Behavior and Human Decision Processes* 91 (2): 254–268.

Warner, D. 2013. Safe de-identification of Big Data is critical to health care. *Managed Care Outlook* (May): 9–10.

Well, A. D. 1971. The influence of irrelevant information on speeded classification tasks. *Perception and Psychophysics* 10 (2): 79–84.

Wilkinson, K. 2013. Usage-based insurance: Fears over privacy or safer streets? *Canadian Business* (October): 1.

Zhao, Y., and N. Harding. 2013. Improving the interpretation of complex audit evidence: The beneficial role of order effects. *Abacus* 49 (4): 476–505.