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Financial fraud detection and big data analytics - implications on auditors' use of fraud brainstorming session

Jiali Tang, Khondkar E. Karim,

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Jiali Tang
Department of Accounting, University of Hartford, West Hartford, Connecticut, USA, and

Khondkar E. Karim
Department of Accounting, Robert J. Manning School of Business, University of Massachusetts Lowell, Lowell, Massachusetts, USA

Abstract

Purpose – This paper aims to discuss the application of Big Data analytics to the brainstorming session in the current auditing standards.

Design/methodology/approach – The authors review the literature related to fraud, brainstorming sessions and Big Data, and propose a model that auditors can follow during the brainstorming sessions by applying Big Data analytics at different steps.

Findings – The existing audit practice aimed at identifying the fraud risk factors needs enhancement, due to the inefficient use of unstructured data. The brainstorming session provides a useful setting for such concern as it draws on collective wisdom and encourages idea generation. The integration of Big Data analytics into brainstorming can broaden the information size, strengthen the results from analytical procedures and facilitate auditors' communication. In the model proposed, an audit team can use Big Data tools at every step of the brainstorming process, including initial data collection, data integration, fraud indicator identification, group meetings, conclusions and documentation.

Originality/value – The proposed model can both address the current issues contained in brainstorming (e.g. low-quality discussions and production blocking) and improve the overall effectiveness of fraud detection.

Keywords Big data analytics, Brainstorming session, Fraud detection

Paper type Research paper

1. Introduction

Financial fraud remains one of the most discussed topics in accounting literature. According to Cotton (2002), the financial scandals of Enron, WorldCom, Qwest, Global Crossing and Tyco resulted in approximately $460bn loss. The detection of financial fraud, therefore, has become a critical task for accounting practitioners.

In the fraud triangle put forward by Cressey (1973), three factors determine the likelihood of fraud occurrence, including pressure, opportunity and rationalization. The core of these factors lies in people's belief and behavior. Due to the unpredictability and uncertainty in fraudsters' incentives and techniques, fraud detection requires the skillset that encompasses both diligence and judgment.

Although the current auditing standards intend to provide a comprehensive guideline that governs the process in fraud examination, the actual implementation is conducted on a

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case-by-case basis that heavily relies on auditor judgment thus leads to inconsistent success rate. For example, AS 2401 contains explanations on understanding fraud, exercising professional skepticism, responding to fraud risk, communicating with the management and documenting auditors' comments[1]. However, these standards might be interpreted and executed differently by auditors, and they cannot effectively address the fraud risk embedded in nonfinancial information (e.g. meeting content, management conversations, tone at the top, language in annual reports, etc.) without competent personnel and supplementary tools.

A recent trend is to apply data analytics to fraud detection. An example is the use of data mining techniques aimed at finding patterns from journal entries to identify fraud (Debreceny and Gray, 2010). While the study contributes greatly to the research on fraud detection method by integrating data and technology, it still ignores the non-numerical signals from parties who prepare the financial statements.

To cope with the flaws mentioned above and provide an addition to the fraud detection toolset, in this paper, we discuss the potential use of Big Data analytics in identifying fraud risk, particularly in the brainstorming sessions required by current auditing standards. In response to the accounting scandals in the early 2000s, an auditing statement aimed at detecting fraud (SAS No.99) was established by AICPA. The standard specifically requires a brainstorming session to be held by auditors to identify fraud-related risks. More recently, the idea of brainstorming has been added to multiple sections of the auditing standards. AICPA mentions in AU-C 240 that the engagement team is required to brainstorm and discuss areas potentially subject to material misstatement, management's fraudulent reporting and asset misappropriation. AU-C 315 of AICPA considers such discussions as auditors' risk assessment activities. Similar requirement is also included in PCAOB standards (AS 2110).

As the purpose of brainstorming is to gather intellectual input from different individuals and inspire new ideas, such format seems to be an effective way of processing unstructured data and capturing anomalies While we believe that brainstorming sessions can enhance the overall fraud assessment, the execution can be quite challenging given the complexity in conducing quality discussions and the limitations contained in the format of brainstorming (e.g. production blocking)[2].

The integration of Big Data analytics provides one solution to improving the performance of the brainstorming sessions. First, Big Data can enlarge the information base used in brainstorming. By combining or aggregating different types of information through Big Data tools, auditors can have access to a database that contains both the financial (e.g. accounting record) and nonfinancial information (e.g. news on management, board meeting minutes, contract details, etc.) of the client firm. Second, Big Data can enhance the information content. When conducting analytical procedures, auditors can efficiently compare data across time and industries to quickly identify anomalies. A larger sample data (or the full population) will also increase the accuracy of the prediction models. Thus, Big Data can generate reliable results that more precisely point to the fraud risks. Finally, Big Data can facilitate the communications among the engagement team members, or even between the predecessor and successor auditors. For example, during the brainstorming sessions, auditors can use electronic devices to record their thoughts while reading other members' comments simultaneously. In addition, Big Data can also incorporate the industry expertise of individual auditors by selectively displaying relevant information (e.g. news, industry index, competitors) on the monitor to inspire new ideas. Overall, the application of Big Data analytics in brainstorming sessions allows auditors to use unstructured data and analyze fraud factors closely related to the fraud triangle. The larger information set and

more reliable evidence help ensure quality discussions, and the computer-based setting can reduce production blocking and redundant process.

To strengthen the practical contribution of our arguments, we propose a model that can be adopted by the audit team engaged in the brainstorming sessions. We suggest a six-step system that includes initial data collection, data integration, fraud indicator identification, group meetings and discussions, drawing conclusions and documentation. We discuss the possible application of Big Data analytics to each step of the process. The model offers an innovative and potentially effective approach of conducting brainstorming and identifying fraud risks.

The remainder of the paper is organized as follows. Section 2 presents the background of fraud detection, Section 3 explains the brainstorming sessions in current auditing standards, Section 4 discusses the application of Big Data analytics, and Section 5 concludes.

2. Financial fraud and issues in its detection

Based on different behavior and consequences, Reurink (2016) classifies financial fraud into three types: financial statement fraud, financial scams and fraudulent financial mis-selling. Of the three categories, financial statement fraud is closely related to bookkeeping and day-to-day transactions as it involves intentional falsification of financial records, inappropriate application of accounting standards, earnings management and other activities that create information asymmetry (Rezaee, 2005). Errors and misrepresentations in accounting record often cause financial restatements. GAO (2002) reports that approximately 10 per cent of the public firms underwent financial restatements during 1997 to 2002. For the other two categories, financial scams refer to the deceptive schemes designed to unlawfully obtain other parties' assets, and financial mis-selling includes deliberately marketing financial products to the unsuitable clients (Reurink, 2016).

Financial fraud has led to tremendous loss over the years. Karpoff *et al.* (2008) show that financial misconduct is penalized by both the legal system and the market, and the latter usually imposes a significantly stronger penalty. Of the 585 firms investigated in their study, the loss incurred in the market due to reputation damage is 7.5 times higher than the legal penalty. GAO (2002) finds that the announcement of restatements triggers a negative market reaction of −10 per cent. Stockholders also respond unfavorably to corporate crimes, especially for companies with similar record previously (Davidson *et al.*, 1994). The consequences of fraudulent activities are not limited to financial loss. Tian *et al.* (2016) show that venture capitalists will face difficulty in obtaining future IPO business if they overlook the fraud in prior cases.

The factors that determine fraud likelihood has been discussed extensively in the literature. Theoretically, Cressey (1973) argues that an individual or organization needs to possess the pressure, opportunity and rationalization (the fraud triangle) to conduct fraudulent activities. Later research proposed a fourth factor, capability, and presented the fraud diamond structure (Wolfe and Hermanson, 2004; Boyle *et al.*, 2015). Power (2013) states that fraud has been considered as a risk rather than an event and discusses the current shift to a universal acknowledgement of fraud risk within organizations. Other factors that have contributed to fraudulent activities include morality (Morales *et al.*, 2014), competition (Bolton *et al.*, 2007), conflicts of interest (Mehran and Stulz, 2007), option-based compensation (Burns and Kedia, 2006; Efendi *et al.*, 2007), clawback adoptions and insider sales (Fung *et al.*, 2015), the knowledge and trust embedded in accounting positions (Dellaportas, 2013) and lack of scrutiny on internal control systems (Baker *et al.*, 2017).

Due to the uncertainty and variability in these factors, fraud detection has become a challenging task that requires both talent and technology. While current auditing standards

(AU 316) put a strong emphasize on exercising professional skepticism, they are perhaps insufficient in addressing the amount of ambiguity and variations in different individuals and organizations. For example, Davis and Pesch (2013) find that the auditors cannot treat fraud detection uniformly without adjustment, and that the detection mechanisms are influenced by organization types and individual social awareness. The incentive to investigate fraud also depends how the reports are framed (Huerta *et al.*, 2012). Trotman and Wright (2012) show that auditors might evaluate external evidence related to fraud based on whether the evidence clashes with business goals, resulting in potential subjectivity. Further, internal auditors can experience stress from reporting to audit committees and alter the level of fraud risk when reporting (Norman *et al.*, 2010). Knapp and Knapp (2001) show that auditors' experience matters in adopting analytical procedures during fraud examination.

To deal with the complexity in fraud detection and enhance effectiveness, different types of technologies are developed and implemented. Some of the highly discussed technology applications include using data mining techniques to find patterns from financial records (Debreceny and Gray, 2010; Grabski, 2010; Gray and Debreceny, 2014), using descriptive data mining tools to identify internal fraud risks (Jans *et al.*, 2010), using outlier techniques to flag fraudulent insurance claims (Capelleveen *et al.*, 2016), using computer algorithms to detect abnormal stock price movement (Williams, 2013) and applying natural language processing (NLP), queen genetic algorithm (QGA) and support vector machine (SVM) to analyze annual reports (Chen *et al.*, 2017).

3. Brainstorming sessions in current auditing standards

Statement on Auditing Standards No. 99 (SAS 99) is a set of standards established in 2002 after the occurrence of the accounting scandals. The statement aims at more effectively preventing and detecting fraudulent activities. One of the highlights of SAS 99 is the requirement of a brainstorming session held by the audit team members. Since then, the standards have been updated and the idea of implementing a brainstorming session has been shown in different parts of AICPA (AU-C 240 and AU-C 315) and PCAOB (AS 2110) standards. According to AU-C 240, the content of the brainstorming sessions should include the occurrence of potential material misstatement, the methods that management might use to commit fraud and the possibility of asset misappropriation. In particular, the session should address management behavior in the context of the fraud triangle (incentive, opportunity and rationalization) and a high degree of professional skepticism must be maintained[3]. Trompeter *et al.* (2013) place brainstorming in the framework of auditors' role in detecting fraud and argue that auditors should consider fraudulent act, concealment and conversion methods during the brainstorming sessions. Based on a survey conducted on 22 auditors by Bellovary and Johnstone (2007), the brainstorming sessions can be summarized as a four-step process, including client information review, fraud triangle analysis, fraud likelihood assessment and audit response indication.

Prior studies have documented several benefits of conducting brainstorming. Osborn (1957) argues that group interactions create stimulation and synergy. Carpenter (2007) concludes that brainstorming auditors can generate new and quality ideas on fraud detection and higher risk assessment relative to individual auditors. Brazel *et al.* (2010) state that fraud risk factors (incentive, opportunity and rationalization) can more effectively indicate fraud likelihood when the brainstorming is high-quality. Hoffman and Zimbelman (2009) find that both strategic reasoning and group brainstorming facilitate the audit procedure modifications.

However, there is also evidence that group interactions cause process loss (Hill, 1982; Straus *et al.*, 2011). Nunamaker *et al.* (1991) list several possible sources of process loss from brainstorming, and three sources are most discussed in the literature, including production blocking, evaluation apprehension and free riding (Dennis and Valacich, 1993). Based on the experiments conducted in Diehl and Stroebe (1987), production blocking appears to be the main cause. Paulus *et al.* (1995) find that group brainstorming can diminish productivity even when members are well-trained in group work.

A further line of research investigates face-to-face and electronic brainstorming. Overall, the studies are in favor of brainstorming conducted electronically. Lynch *et al.* (2009) show that computer-mediated brainstorming sessions enhance the effectiveness of fraud risk assessment. Specifically, electronic brainstorming can mitigate concerns such as production blocking, evaluation apprehension and free riding, and strengthen synergy during interactions (Dennis and Valacich, 1993). Additionally, Smith *et al.* (2012) state that the superior performance of electronic brainstorming is mainly due to stronger task focus and longer comments made by auditors. In particular, computed-based groups and group support systems (GSS) have demonstrated strong performance in tasks related to idea-generation (Valacich *et al.*, 1994; Fjermestad and Hiltz, 1998).

Literature has also shown some benefits of face-to-face brainstorming. For example, Cockrell and Stone (2011) find that face-to-face brainstorming encourages more in-depth discussion that leads to better performance than electronic format. Brazel *et al.* (2004) show that face-to-face audit workpaper review is associated with more accountability and higher quality judgment from the preparers relative to the review in electronic mode. Overall, face-to-face brainstorming seems to suffer more from process loss, particularly production blocking, while electronic brainstorming might result in low-quality dialogue and judgment.

4. Application of big data analytics

Based on the above, financial fraud is the product of internal and external factors that involve incentives, opportunities and rationalization. The detection mechanism is complicated and tends to overlook clues from non-financial information. The auditing standards introduce a critical mechanism in fraud assessment, the brainstorming sessions, which allow auditors to draw on collective wisdom and generate ideas. In this section, we discuss the integration of Big Data analytics into the brainstorming sessions.

The meaning of such integration is twofold. One is to propose detailed procedures that can make use of the non-financial information in detecting fraud. The fraud triangle emphasizes incentives, opportunity and rationalization, all of which involve a high degree of uncertainty and cannot be identified simply through the numbers on the financial statements. Big Data analytics can be useful in this dimension by incorporating unstructured data and providing more reliable results. The other purpose is to address the concerns in both face-to-fact and electronic brainstorming. As mentioned above, the effectiveness of brainstorming can be compromised due to production blocking and lack of in-depth discussions. The use of Big Data can, at least to some extent, mitigate these problems and eventually enhance the effectiveness of fraud detection.

Big Data is usually defined as possessing the characteristics of four Vs, namely, Volume, Velocity, Variety, Veracity (Zhang *et al.*, 2015), and requires the support of large, complex information systems (Vasarhelyi *et al.*, 2015). Yoon *et al.* (2015) argue that Big Data provide sufficient, reliable and relevant information that should be considered as complementary audit evidence. Big data also increase audit quality due to its ability to enable population-based audit compared to sample-based (Ramlukan, 2015). While the application of Big Data in accounting and auditing practice has been introduced before (Tang and Karim, 2017), the

focus on brainstorming sessions remains undiscussed and could generate useful implications.

We propose three channels through which Big Data can be used in brainstorming. First, Big Data can combine structured and unstructured data. A key part of the brainstorming session is to review and analyze the client's prior information in the framework of the fraud triangle. Thus, the information should be presented in various formats that can effectively indicate fraud risk factors. Prior studies support the use of nonfinancial measures (Brazel *et al.*, 2009) and text-mining method (Humphreys *et al.*, 2011) in fraud assessment.

For example, the news related to management, board members, employees and company-wide reputation can be selectively combined with the firms' financial record to provide more complete evidence. The observation that a CEO increases personal spending on luxurious items when the company is incurring a loss and layoff should serve as a potential fraud risk. Board meeting minutes can also be extracted and matched with the actual outcomes. Auditors can check whether the agenda is indeed carried out by gathering evidence from different sources. In addition, Big Data can help auditors examine alumni relationships, especially those between managers and audit committee members. Information derived from social media can assist auditors in identifying appointments or new positions obtained through personal network, which often leads to fraudulent activities. The messages from anonymous whistleblowers can also be analyzed as an additional source of information. Kaplan *et al.* (2012) show that non-anonymous whistleblowers are discouraged from reporting when they witness no repercussions to the fraudsters. With the help of Big Data technology, the brainstorming sessions can combine the whistleblowers' information with data in other formats, which retains the confidentiality and increase evidence completeness.

In short, Big Data provides a larger and more resourceful information base that enables auditors to efficiently translate audit evidence into fraud risk factors. The integration of unstructured data also enhances the veracity of audit evidence. The reason is that data collected in such large quantity and from very different sources offer more complete evidence compared to the traditional data and are subject to less management manipulation.

Second, Big Data can enhance the performance of analytical procedures, thus yielding more insightful and reliable results for decision-making. In trend/pattern analysis, all accounting data can be pooled and compared across years and industries. Perols and Lougee (2011) find that earnings management in prior years is an indicator for committing fraud. Accordingly, auditors can conduct regression analysis to find associations on the population level to increase the model's explanatory power. Big Data can also be useful in identifying anomalies. Kedia and Philippon (2009) show that firms involve in earnings management tend to invest aggressively to match the performance of the better firms in the industry. Auditors can use computer algorithms to detect any sudden change in profits or revenue that falls out of the normal range of the industry average. PCAOB (2007) states that the performance of analytical procedures can be strengthened if the data analyzed are subject to less manipulation. By gathering timely raw data from real-life sources, auditors are presented with more reliable information thus improving the relevance of the ideas generated during the brainstorming process. That is, Big Data analytics tools can significantly contribute to the brainstorming sessions if they are designed to provide timely and accurate feedback upon auditors' request.

Finally, Big Data can facilitate the communications during brainstorming sessions. Building on the idea of electronic brainstorming, Big Data can further incorporate computerized programs to record fraud discussions, trace the chain of thoughts and establish possible scenarios. Auditors can write down longer comments that include photos, flowcharts and videos to express their ideas. Devices can be used to simultaneously record

all auditors' comments and present them on the same screen. The devices can be programmed to combine the unstructured data and group auditors' comments into categories. Analysis, such as descriptive data mining, can then be performed within each category to generate conclusions. Therefore, Big Data analytics not only eliminates the wait time for speaking during discussions, a common issue in face-to-face brainstorming, but also allows auditors to quickly use dialogue in idea generation.

In addition, Big Data can collect the comments from both predecessor and current auditors and draw on prior fraud cases occurred in real life. This allows auditors to trace the thought pattern of potential fraudsters and construct hypothetical fraud scenarios. Further, Big Data tools can research on each auditor's industry background and work experience. Displaying information such as news reports and industry index can provide auditors with a sense of familiarity and inspires logical and creative thinking.

To summarize, the above procedures require careful design and an efficient combination of Big Data, technology and accounting professionals. Such integration can help mitigate concerns found in brainstorming (e.g. production blocking and low-quality discussions) and use non-financial and unstructured data to better identify fraud factors within the framework of the fraud triangle.

Following the advantages mentioned above, we propose a model that can effectively incorporate Big Data analytics in the brainstorming sessions. The model contains six steps, and the performance at each step can be enhanced by the suggested application of Big Data tools, as shown in Figure 1.

Step 1 and Application 1: The brainstorming process should begin with initial data collection that helps uncover potential fraud indicators, which later serve as the outline for the group meetings. The system can automatically generate pre-saved data queries that contain the company's basic information, such as business operations, financial statements, prior audit results, board composition and recent media coverage. Further data requests for specific items can be submitted by members of the audit team based on their experience, and the system will populate the results along with the original request. For example, an audit team member might suspect the existence of a close relationship with the supplier could lead to bribery or kickbacks. Therefore, the detailed purchase history with the supplier should be

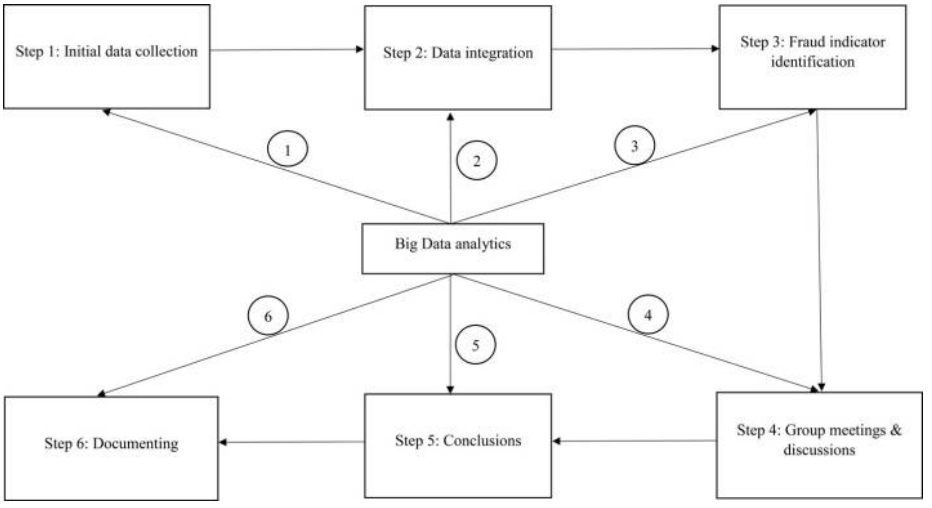

Figure 1.
Proposed model for the application of big data analytics to the brainstorming session

added to the query. If a firm's revenue performance consistently beats external expectation, it could be a signal of earnings overstatement and source documents that support the sales transactions should be collected. In short, Big Data analytics can facilitate the data collection task by searching and storing a large amount of data in different formats.

Step 2 and Application 2: data in various formats collected in Step 1 are processed. The main objective of this step is to combine the structured and unstructured data so a unified version of suitable evidence can be presented. For example, surveillance video can be combined with inventory record to detect risk in inventory theft. The software can also merge data of system logs with high-risk accounts such as cash to discover unauthorized access and fraudulent activities.

Step 3 and Application 3: based on the data collected and organized in the previous steps, some primary analytical tasks can be performed to identify potential risk factors. The application of Big Data analytics in such analysis varies across companies and industries. For banks and financial service companies, a close examination of the high default rate loans (e.g. type, loan amount, interest rate, location, account managers) can reveal the business line with high fraud risk. In an environment where intellectual properties are susceptible to theft, tests can be conducted to distinguish patterns, such as the number and type of similar products released around the same time by competitors. This helps uncover the department and product line that require stronger security checks and protection systems. In the insurance industry, analysis can be carried out to identify irregularities in billing activities. If a department consistently processes insurance claims right before the policy lapses, it might be a signal of potential fraud committed by the insurers, which should trigger further auditing work.

Step 4 and Application 4: the audit team can then coordinate group meetings, in which the previously identified risk factors are used for idea stimulation and inspiration. The purpose of incorporating the fraud indicators determined by Big Data tools is to provide helpful guidelines and build relevant context so that new ideas are more likely to be generated. The system-identified risk factors should not serve as a checklist that limits the scope of the audit team's discussion. Rather, they should provide additional evidence that could not be captured by auditors' intuition.

Even when the technology can establish an extremely secure environment, such as blockchain, it is impossible to eliminate all risk factors, which makes manual monitoring necessary. For example, while companies that adopt blockchain technology seem to contain almost zero risk due to the difficulty in altering transaction records, auditors should still consider the potential flaws in the system design. A dominating miner node could control the blockchain to commit fraud, and identity theft can comprise the entire network (Xu, 2016). Hence, the existence of Big Data tools should serve to complement auditors' professional judgment.

The effect of the group meetings can be further enhanced by the continued use of Big Data tools throughout the discussion process. For example, similar fraud cases in the past can be requested and presented during meetings for comparison. A Big Data software can record each person's thoughts, questions and notes simultaneously and display them on the same screen for the team to share. Team members can follow-up with an analytical test when new comments emerge to solidify the proposed ideas. Auditors can also use the massive database to explore hidden clues and reconcile different opinions as they proceed with the brainstorming. In short, the incorporation of Big Data encourages group members to delve into new areas and offers instant data support.

Step 5 and Application 5: in this step, new ideas proposed during the group meetings are evaluated and finalized. With the assistance of recording devices, each team member can

view the ideas of others and leave comments. The system can categorize the auditors' comments into different sessions according to the content and tones. Within each session, the software can collect additional data to perform analytical procedures. These procedures can address questions include: are the concerns raised by auditors supported by real-life cases? Is the fraud indicator particularly relevant to a specific industry? Can we observe a pattern from similar fraud cases? Further, an anonymous voting on the mostly mentioned ideas can be conducted. Based on the feedback provided by team members and data analysis, the audit partner/leader can then proceed to draw the conclusions.

Step 6 and Application 6: the final step completes the entire process by documenting the content and results of the brainstorming sessions. While the conclusions reached by the audit team remain the most important product, it is also necessary to document the detailed thought process of each team member. As Big Data tools can store and combine data in various formats, even voice and video records of the group meetings can be properly saved. These "work-in-progress" notes from the discussion will help form a useful source of database for future brainstorming sessions.

The implementation of the proposed model will require some necessary training, both on auditors' knowledge of current Big Data trends and their skills in using technology that is compatible with handling audit tasks. A separate department can be established to design the system, and workshops can be organized to teach members helpful techniques. The training should be systematically conducted and offered to all auditors, particularly for the audit partners who might lead the brainstorming discussions. Given the scale of resource and revenue, Big 4 might be more suitable candidates to adopt the model at the current stage. However, there is essentially no constraint on making the choice as long as the budget allows, or the client's business operations demand a Big-Data-supported audit.

We further discuss the potential benefits and extension of the model above. According to PCAOB (2007), the effectiveness of brainstorming can be impaired when the session was not properly held, or key members were absent. By incorporating Big Data tools, the brainstorming session can be conducted remotely, which encourages more participation. As the comments are recorded and processed in the system, the content of the meetings can be shared via a network when a member fails to attend. This also allows continuous discussion and communication among the engagement team, especially when new ideas or facts are discovered after the planning stage.

However, the integration of Big Data in brainstorming sessions should be conducted with caution to avoid interacting with factors that negatively affect auditors' judgment. Simon *et al.* (2018) find that the separation of likelihood and magnitude assessment of risk, as recommended by the auditing standards, actually results in worse auditor's judgment. Rose *et al.* (2017) find that Big Data visualizations should be introduced after the traditional audit evidence to yield positive results. These findings suggest that the design of a Big-Data-supported brainstorming session should consider auditors' cognition and behavior.

Finally, the proposed integration of Big Data tools can be extended to different steps of the audit process. For example, initial data collection (Step 1), data integration (Step 2) and fraud indicator identification (Step 3) can be used in the planning stage to establish the scope of the audit and risk assessment procedures. Hammersley *et al.* (2010) find that documentation specificity during planning stage affects the subsequent fraud risk assessment; thus, documenting (Step 6) of the model can be helpful in this task. For substantive testing, analytical procedures using Big Data technology described in Step 3 can be carried out to detect material misstatement. The review stage can benefit from Step 3 and Step 6 so auditors can have easy access to the previously discussed memos and performance effective analytical procedures when assessing the conclusions.

5. Conclusions

This paper discusses the application of Big Data analytics to the brainstorming sessions required in the current auditing standards. We review literatures on the causes and consequences of financial fraud. We further comment on the existing problems in fraud detection mechanisms, particularly the difficulty in analyzing unstructured and non-financial data. The brainstorming sessions offer a potential solution by encouraging discussions and new ideas. Given the complexity in organizing individual thoughts and drawbacks in the format of brainstorming, whether it is face-to-face or electronic, we propose the integration of Big Data analytics into the brainstorming sessions. The obvious advantages of such integration include comprehensive information base, useful results from analytical procedures and efficient communications. Our proposed model outlines a six-step brainstorming process that can benefit from the application of Big Data analytics.

One limitation of the model proposed is its cost-effectiveness. The implementation of Big Data tools during brainstorming sessions and other parts of the audit process can be costly, particularly given the need to continuously update the system and collect various types of data. Moreover, the choice of integrating Big Data tools partially depends on the audit fees and whether the clients themselves use Big Data technology in the accounting practice. This implies that larger audit firms with stronger revenue performance are perhaps more suitable candidates to adopt the model. Another caveat is that the quantity of Big Data might create unwanted burden for the engagement team. As stated in Appelbaum *et al.* (2017), if an audit by exception (ABE) approach is adopted, Big Data can generate too many exceptions which hinder the audit process. Brown-Liburd *et al.* (2015) identify information overload and relevance as potential drawbacks of Big Data. This implies that adjustments to the overall audit strategy need to be made if auditors decide to involve Big Data tools in the audit process. Finally, the security of Big Data also deserves attention. Appelbaum (2016) argues that the provenance of audit-related data should be safely managed so that the auditors can retrace the events for verification purpose. The same might apply to using Big Data tools in the brainstorming sessions, which is to emphasize the importance of verifying the source of all data.

Future research can be conducted in areas that extend the arguments in this paper. For example, theoretical framework with respect to the application of Big Data analytics should be developed. Alles and Gray (2016) argue that Big Data can be interpreted incorrectly and generate false positives without formal theories for guidance. Other potential questions include: what are possible sources of the unstructured data considered in the brainstorming sessions? What analytical procedures can be developed using Big Data tools? What are the advantages and disadvantages of the existing brainstorming methods and future ones that incorporate Big Data? We suggest future studies use survey results or case analysis to address these questions.

Notes

1. Please refer to the official website of PCAOB, available at: https://pcaobus.org/Standards/Auditing/Pages/AS2401.aspx
2. Production blocking refers to the situation within a group where only one member can speak at a time. This consequently leads to wait time for other members (Diehl and Stroebe, 1987).
3. Please refer to the official website of AICPA, available at: www.aicpa.org/Research/Standards/AuditAttest/DownloadableDocuments/AU-C-00240.pdf

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About the authors

Jiali Tang is an Assistant Professor of Accounting at the University of Hartford. Her research interest includes earnings quality, corporate governance, audit quality and corporate social responsibility. Jiali Tang is the corresponding author and can be contacted at: jtang@hartford.edu

Khondkar E. Karim has published over 80 articles in various refereed journals including *Accounting Organizations and Society (AOS)*, *Behavioral Research in Accounting* (*BRIA*), *Journal of Corporate Finance, Accounting Horizons*, *Journal of Accounting Auditing and Finance*, *Managerial Auditing Journal*, *Review of Quantitative Finance and Accounting*, *Applied Financial Economics*, *Advances in Accounting Behavioral Research*, *International Journal of Finance*, *Advances in Accounting, Advances in International Accounting*, *Advances in Quantitative Analysis of Finance and Accounting*, *Research in Finance*, *International Journal of Auditing* and *The Mid-Atlantic Journal of Business*. He is also the recipient of a 1999 ANBAR Citation of Excellence for AOS paper. He has received the outstanding teaching award and outstanding research award in 1997 and 1999 respectively. He was recognized as one of the most productive accounting doctoral graduates in a study published in Advances in Accounting. It identified the top ten doctoral graduates by the year of their graduation and the number of publications within the top 40 selected accounting journals. He has co-edited a monograph on environmental disclosure practices and financial performance and two special issues of managerial finance on performance measurement and evaluation. He served on the editorial board of *Issues in Accounting Education*. Currently, he serves as the Editor of *Advances in Accounting Behavioral Research*.