The use of Big data analytics and artificial intelligence tools to prevent fraud in the audit field: A conceptual frame

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ABSTRACT: During the past decades, because of several financial scandals the problem of fraud and fraud detection has become more relevant, involving investors, organizations and other stakeholders. In this respect, the role of the auditors and forensic accountants became pivotal in order to guarantee fraud detection and to minimize the expectation gap. The digitalization of firms' activities, known as "industry 4.0", includes the audit process too. Big Data analytics and artificial intelligence can be used with the aim of identifying and preventing fraud. The goal of this article is to analyse the adoption of Big data and artificial intelligence technique in the fraud auditing environment through the review of the existing literature on the matter, the possible adoption of Big data and artificial intelligence is discussed.

KEYWORDS: Fraud auditing, fraud, Big Data, Artificial intelligence, Industry 4.0.

Introduction

Great financial scandals such as Enron, WorldCom, Global Crossing and Parmalat that took place during the past decades together with their implication in the huge mistrust of the investors in the financial market and the economic and financial crises have putted into the spotlight the problem of fraud and fraud detection (JONES 2010, SINGLETON 2010, MIRONIUC et al. 2012). Both practitioners and academics have faced with the matter trying, on one hand, to conceptualize the reasons of frauds' commissions in accounting environment (RIAHI-BELKAUOI et al. 2000, CRUTCHLEY et al. 2007) and on the other hand, to identify fraud detection modelling (MATSUMURA et al. 1992, GOPINATHAN 1998, BOLTON et al. 2002, PHUA et al. 2010).

In the accounting and auditing international literature, a lot of attention is paid in considering auditors' responsibility for fraud detection in terms of professional scepticism and risk assessment procedures and in the evaluating of the effectiveness of audits in identifying fraudulent misstatements in financial statements (KNAPP et al. 2001, SHELTON Et al. 2001, RAMOS, 2003, ASARE et al. 2004, CARPENTER 2007, VONA 2012).

In addition, another branch of the literature emphasises the role of forensic accounting and forensic accountants in deterring, preventing and investigating fraud (OKOYE 2009, HUBER 2017, KRANACHER et al. 2019, HOPWOOD et al. 2012). A quite unexplored research topic deals with the application of new technologies, such as big data analytics and other data mining technique as a tool for the auditors to prevent frauds' commission. The main goal of the article is to fill this gap, conceptualizing, through a review of the existing literature on the matter, the adoption of Big data and other data mining technique such as artificial intelligence tools, in the audit domain with the aim of preventing and identifying fraud.

To achieve this aim the rest of the article has been organized according to the following fashion: the second paragraph browses through the meaning of fraud auditing and forensic accounting; the third paragraph discusses the adoption of the paradigm "industry 4.0" and the application of Big data analytics and artificial intelligence in different contexts.

In the fourth and fifth paragraphs, the application of Big data and artificial intelligence in the audit domain with the aim of detecting fraud is discussed. The sixth paragraph highlights the limitations related to the adoption of Big data technique and artificial intelligence in auditing. Finally, the conclusion section is presented, highlighting the limitation of the study and future research directions.

1. Fraud auditing and forensic accounting

The accounting literature provides several definitions of the terms fraud auditing and Forensic accounting. Fraud auditing is a branch of the auditing field which involves "specialized approach and methodology to discern fraud" (SINGLETON et al. 2006: 3) while forensic accounting refers to the "comprehensive view of fraud investigation" (SINGLETON et al. 2010: 12). In particular, the forensic account is someone who has a huge expertise and knowledge in the different process of fraud investigation (SINGLETON et al. 2006). Other definitions in the accounting literature are provided. Some authors defined Forensic accounting as "a science dealing with the application of accounting facts gathered through auditing methods and procedures to resolve legal problems" (SIEGEL et al. 2010). Others emphasise the investigative and suspicious mind of the Forensic accountants (ALBRECHT et al 2011). Many highlight that Forensic accounting is "the practice of rigorous data collection and analysis in the areas of litigation support consulting, expert witnessing, and fraud examination". (REZAEE et al 2004). A comprehensive definition is provided by the AICPA that considers Forensic accounting as "Services involving the application of specialised knowledge and investigative skills possessed by CPAs to collect, analyse and evaluate the evidential matter, and to interpret and communicate findings in the courtroom, boardroom or other legal or administrative venues" (BOTES et al. 2018). In the auditing field, forensic accounting is related to the application of auditing methods, techniques or procedures applied in order to resolve legal issues (KOH et al. 2009).

Fraud auditors as well are auditor endowed with knowledge, skills and expertise at detecting and documenting fraud (SINGLETON et al. 2006).

Several studies took in consideration in a great detail, what kind of skills a professional forensic accountant and fraud auditor should acquire (OZILL 2015). Core skills are skills considered to be fundamental to become a forensic investigator.

Other Authors stressed the importance of forensic accounting education especially provided by academic institutions, emphasising how, the opportunity for students to acquiring forensic accounting knowledge and skills during their academic programmes improve their capability in terms of detecting fraud (REZAEE et al. 2004; REZAEE et al. 1997, KRANACHER et al. 2008; EFIONG 2012, KRAMER et al. 2017, REZAEE et al. 2016, SEDA et al. 2008).

2. The paradigm "industry 4.0" and the application of Bid data and artificial intelligence in different domain

The term "Industry 4.0" refers to the application of highly mechanized and automatized techniques to the manufacturing industry and the production of goods (LASI et al. 2014).

This word was originally coined with reference to the German industrial revolution involving the mentioned digitalized processes that took place around 2011 (LIAO et al. 2017). Industry 4.0 is linked to social, economic and political changes, which consist with (LASI et al. 2014): 1) short development periods; 2) individualization on demand; 3) Flexibility; 4) Decentralization. To realize this objectives there are nine "pillars" that firms can adopt (RÜßMANN et al. 2015): 1) Big Data and Analytics; 2) Autonomous Robots; 3) Simulation; 4) Horizontal and Vertical System Integration; 5) The Industrial Internet of Things; 6)Cybersecurity; 7) The Cloud; 8) Additive Manufacturing; 9) Augmented Reality. In this respect, Big Data and artificial intelligence are two of the technique one can apply to achieve an industry 4.0 system. During the past few years, this automatized production process is not just related to the manufacturing firms but defines a new level of organization and control, which involves the entire value chain (VAIDYA et al. 2018). In particular, these innovative processes involved accounting and auditing too (ANTONEY et al. 2019). There are a number of applications of Big Data and Artificial Intelligence outside of the auditing and accounting field. According to many, big data and artificial intelligence can perform together in order to improve real time production logistics (DAVIS et al. 2020).

In marketing studies, automated Artificial intelligence agents powered by machine learning technique can be used to analyse unstructured big data to extract information about business and to map costumers purchase journeys in order to improve decision making processes (MA et al. 2020). Another example of the unified application of machine learning and big data outside of the audit domain is the use of supervised and unsupervised machine learning techniques for efficiently analysing a big volume of crime data (WANG et al. 2016).

3. The use of Big data analytics in the audit domain

3.1. The meaning of Big Data

The most common definition of Big Data identify them as "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" (GARTNER 2013). This definition emphasizes some specific features of Big Data. In particular, while the "high volume" of the data is related to their huge size (MOFFITT et al. 2013), the high velocity faced with the speed in which data were provided and the "high variety" refers to the large amount of sources to which they come from (ZHANG et al. 2015, ARNABOLDI et al. 2017, YOON et al. 2015, VASARHELYI et al. 2015). In this respect, they included structured and unstructured data coming from different type of sources such as website, social media, videos or photos and emails (SYED et al. 2013, ARNABOLDI et al. 2017, ZHANG et al. 2015). Other Authors defined Big Data as "datasets so voluminous they cannot be reasonably analyzed using database management systems or traditional software programs" (WARREN et al. 2015, MCKINSEY 2011). Collection and analysis of these data, in the form of Video, image data, audio data textual data is pivotal in modern organizations in order to support decisions' making processes (VASARHELYI et al. 2015, WARREN et al. 2015).

The process of inspecting, cleaning, transforming, and modelling Big Data to discover and communicate useful information and to separate them form the useless ones in order to support decision making processes is called *Big Data analytics* (CAO et al. 2015).

3.2. The adoption of Big Data: Challenges and opportunities for the auditors

The use of Big Data analytics in the accounting field is fundamental. Several studies considered the implications of introducing Big Data in accounting and auditing studies and practice (ZHANG et al. 2015, ARNABOLDI et al. 2017, YOON et al. 2015, VASARHELYI et al. 2015, CAO et al. 2015, WARREN et al. 2015). A number of application for Big data analytics are identified. Firstly, some Authors shed light on the fact that Big data will significantly change accounting with particular mention to financial accounting quality as well as the relevance of accounting information (WARREN et al. 2015, AL-HTAYBAT et al. 2017). In particular, Big Data, in respect to financial statements, can improve transparency and usefulness for decision making (WARREN et al. 2015). From the auditors' viewpoint, there are several application of big data as well. Someone suggested the use of Big Data as "audit evidence" (YOON et al. 2015). The audit evidences are all the sets of information that the auditor need to acquire during the audit process in order to decide if financial statements have been kept in accordance to the accounting principles. In this respect, Big Data represent fundamental audit evidence because of their sufficiency relevance and reliability (YOON et al. 2015, Vasarhelyi et al. 2015). These features are significantly better compering with traditional audit evidence. In addition, the major facilitator for the use of Big data as a source of audit evidence is the openness of audit standards to sources of audit evidence different from the traditional general ledger data (ALLES 2015). The use of Big Data makes possible for the auditors to analyse larger population of data to acquire financial and nonfinancial information (BROWN-LIBURD et al. 2015). Other Authors (CAO et al. 2015) identified several application of Big Data in the audit process connected to different audit phases such as identifying and assessing the risks associated with accepting or continuing an audit engagement or performing substantive analytical procedures in response to the auditor's assessment of the risks of material misstatement.

3.3. The use of Big Data in fraud auditing

Big data analytics can be usefully used when there is a deficiency of "traditional" audit evidence gathering mainly through financial information, in the case of fraud detection (BALIOS et al. 2020, TANG et al. 2019, DAGILIENE et al. 2019, YOON et al. 2015, CAO et al. 2015, VASARHELYI et al. 2015). Acquiring evidence of an existing fraud can be difficult considering that great part of this evidence is related to management's lifestyle, ethics and moral value (YOON et al. 2015). In addition, fraud represents a very small percentage of transactions and this is the reason why they could be easily not included in sample that auditors selected (ALLES et al. 2016). Big data represent rich data sources useful to identify potential fraudulent activities rendering too difficult for fraudster to cover the fraud committed in the financial statements (ALLES et al. 2016). In this respects, thanks to the analytic nonfinancial data and nonfinancial measures can be use as variables to develop predictive tools able to aid auditors in detecting fraud (LITTLEY 2012, EARLEY 2015). The analysis of nonfinancial information can be enlarged also to personal emails (HOLTON, 2009) A possible use of Big Data to prevent fraud, for example, deals with money laundering operations (LOKANAN, 2019, BROWN-LIBURD et al. 2015, ALLES et al. 2016). Such a situation is described by Brown-Liburd et al. 2015. They emphasise that "*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*".

Big data analytics can be used also in order to obtain evidence about fraud using financial information.

Fay et al. 2017 emphasised the power of Big Data while performing a procedure that is required on all financial statement audits – an analysis of journal entries for evidence of fraudulent financial reporting (FAY et al. 2017).

All this aspects shed light on the importance of integrating Big Data topics in the Forensic accounting curricula (REZAEE et al. 2018).

4. Artificial intelligence technique

4.1. What is Artificial intelligence?

Artificial intelligence can be defined as "a branch of computer science that deals with the automation of intelligence behaviour" (LUGER 2005). It includes several technique such as machine learning and deep learning (CAMPESATO, 2020).

For the audit area, "we can define artificial intelligence as a hybrid set of technologies supplementing and changing the audit" (ISSA et al. 2016).

4.2. The use of artificial intelligence in auditing and its application in fraud detection

There are a number of studies considering the application of artificial intelligence and expert systems in the audit and accounting field (KOKINA et al. 2017, RAPHAEL 2017, ISSA et al. 2016, OMOTESO 2012, BALDWIN et al. 2006, KOSKIVAARA 2003, BAILEY et al. 1987, VASARHELYI et al. 1998, O'Leary et al. 1997).

Artificial intelligence is mainly used in audit domain in order to automatize labour – intensive activities (KOKINA et al. 2017). There are several repetitive tasks in the audit process that were, traditionally, performed manually and which required a huge amount of work in terms of time with particular mention of substantive tests (ABDOLMOHAMMADI 1999). There are several application for artificial intelligence technique in the audit process. Some Authors discussed the use of artificial intelligence tools, such as neural networks, in analytical review procedures and risk assessments (BALDWIN et al. 2006).

Regarding the application of artificial intelligence to detect fraud, some studies emphasised the use of decision aids in the decision process of assessing the risk of management fraud (EINING et al. 1997). Neural networks as well have been used to assess the risk of management fraud (GREEN et al. 1997, Koh 2004). Other Authors developed a classification model based on machine learning to help auditors to predicting the fraudulent firms on the basis of present and historical risk factors (HOODA et al. 2020).

5. Limitations linked to the adoption of Big data and artificial intelligence in auditing and fraud auditing

Despite the numerous benefits associated with the introduction of Big data and artificial intelligence in auditing and fraud detection, there are several issues linked to their adoption that needs to be assessed. Firstly, while automated audit procedures could allowed the auditor to save time, reducing highly time-consuming activities, on the other hand this adoption could increase auditor unemployment (TIBERIUS et al. 2019). Nevertheless, according to many, this switch from traditional auditing process to digitalized and automatized auditing process will not diminished the role of the auditors that will still be competent for the evaluation of anomalies creating a sort of "auditing by exceptions" (CHIU et al. 2014). Another issue is related to the high investments in terms of money, human resources and research that audit firms need to deal with in order to realize a fully digitalized audit system (CHAN et al. 2018). Finally, the adoption of Big data as audit evidence to identify fraudulent behaviour, could meet limitation in information privacy (YOON et al. 2015).

The major concerns individuals have with mention to information privacy is related to unauthorized secondary uses of data (SMITH et al. 1996).

6. Conclusion

The article reviewed the literature about the use of Big data and artificial intelligence in the audit domain with the aim of identifying and preventing accounting fraud. Both big data and artificial intelligence can be usefully applied in fraud detection. Big data represent a more sufficient reliable and relevant audit evidence compering with the traditional evidence acquired by the auditors during the audit process. Also in terms of fraud detection, Big data allow a better understanding of the financial and nonfinancial information. In addition, Big data analytics can be used in order to make prediction. Artificial intelligence, especially neural network, can be applied in risk assessment activities and in making prediction to preventing fraud. The study suffers a number of limitations. Firstly, in the article only the application of big data and artificial intelligence in fraud auditing has been considered, overlooking the adoption of the other "pillars" of industry 4.0. Secondly, to better understand the role of Big data and artificial intelligence to prevent fraud, an analysis of empirical use of these techniques in the audit firms is due.

These limitations can represent future research directions and opportunities to develop our research on the matter.

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