# DETECTING AND PREVENTING FRAUD WITH BIG DATA ANALYTICS: AUDITING PERSPECTIVE

Ida Rosnidah [*], Razana Juhaida Johari [**], Nurul Afifah Mohd Hairudin [***], Sayed Alwee Hussnie Sayed Hussin [****], Ayatulloh Michael Musyaffi [*****]

* Faculty of Economics, Universitas Swadaya Gunung Jati, Cirebon, Indonesia
** *Corresponding author*, Faculty of Accountancy, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
Contact details: Faculty of Accountancy, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia
*** Esco Micro (M) Sdn Bhd, Shah Alam, Selangor, Malaysia
**** National Audit Department of Malaysia, Putrajaya, Malaysia
***** Faculty of Economics, Universitas Negeri Jakarta, Jakarta, Indonesia

**How to cite this paper:** Rosnidah, I., Johari, R. J., Mohd Hairudin, N. A., Hussin, S. A. H. S., & Musyaffi, A. M. (2022). Detecting and preventing fraud with big data analytics: Auditing perspective. *Journal of Governance & Regulation, 11*(4), 8–15. https://doi.org/10.22495/jgrv11i4art1



**ISSN Print:** 2220-9352
**ISSN Online:** 2306-6784

**Received:** 06.01.2022
**Accepted:** 25.08.2022

**JEL Classification:** M4
**DOI:** 10.22495/jgrv11i4art1

## Abstract

Fraud exposes a business to a variety of significant financial risks that can threaten both its profitability and public image. All firms are almost certain to be victimized by some form of economic crime or fraud. As a result, the business world's revolution in big data and data analytics plays a critical role in the establishment of competitive companies, as big data is already being used in a wide variety of industries (Rezaee & Wang, 2019) and is referred to as the next frontier in terms of productivity, innovation, and competition (Al-Marzooqi, 2021). This paper aims to explore how auditors use big data analytics to detect and prevent fraud in their audit work, the benefits, and barriers of incorporating big data analytics into audit practice. Methodologically, this study conducted a library search and evaluated prior literature reviews on the subject of big data analytics and the auditing profession. The resources span a range of items, from online and print sources to articles in journals and chapters in books. Numerous databases, including Scopus, Web of Science, Science Direct, and Google Scholar, were searched between 2011 and 2022 to compile literature on the subject. This paper makes recommendations on how to improve data analytics approaches for detecting and preventing fraud as well as discusses limitations and future studies.

**Keywords:** Big Data, Data Analytics, Fraud Prevention, Fraud Detection, Auditing

**Authors' individual contribution:** Conceptualization — I.R. and R.J.J.; Methodology — N.A.M.H.; Resources — N.A.M.H., S.A.H.S.H., and A.M.M.; Formal Analysis — R.J.J. and N.A.M.H.; Writing — Original Draft — I.R. and N.A.M.H.; Writing — Review & Editing — I.R. and R.J.J.; Supervision — I.R.; Project Administration — N.A.M.H., S.A.H.S.H., and A.M.M.

**Declaration of conflicting interests:** The Authors declare that there is no conflict of interest.

**Acknowledgements:** The Authors gratefully acknowledge Universitas Swadaya Gunung Jati (Indonesia), Universiti Teknologi MARA (Malaysia), Esco Micro (M) Sdn Bhd (Malaysia), National Audit Department of Malaysia, and Universitas Negeri Jakarta (Indonesia) for all supports and resources.

## 1. INTRODUCTION

The goal of fraud detection and prevention is to isolate unethical behaviors all around the world. Big data is considered the wave of the future not only in business but also in accounting firms, and any company that lags behind in the development of data analytics capabilities and innovation is likely to fall behind the competition and suffer severe financial consequences. Furthermore, accounting firms have stated that big data is becoming an increasingly important aspect of their assurance process since it aids in the detection and prevention of fraud.

Big data denotes extremely large amounts of data that cannot be efficiently processed using existing applications. It is a tool that may be used to examine data and make better decisions and strategic business decisions. Big data is described as high-volume, high-velocity, and high-variety data assets that necessitate cost-effective, innovative data processing for improved insight and decision-making (Gartner, 2013). The volume of information that a system must process and transmit, the pace at which information increases or disappears, and the variety of data sources and formats are all included in the definition. In addition to the three dimensions identified by Gartner (2013), Hadi, Shnain, Hadishahee, and Ahmad (2015) discussed another two dimensions of the big data characteristics, namely veracity and value, which refers to the uncertain and doubtful dependability of data sources and the added value that the collected data can bring to the intended process, activity or predictive analysis/hypothesis, respectively.

Data processing in the 1960s, information applications in the 1970s–1980s, decision-support models in the 1990s, data warehousing and mining in the 2000s, and big data in today's environment demonstrates the growth of IT-enabled decision-support systems (Kim, Trimi, & Chung, 2014). Furthermore, the current decade (2010–2019) appears to be destined to be known as "The Decade of Big Data" (Gillis & Stephanny, 2014, p. 2). Data analytics, on the other hand, is the process of examining, cleansing, transforming, and modeling large amounts of data in order to uncover and communicate useful information and patterns that can be used to draw conclusions and support decision-making, often with the help of specialized systems and software.

According to Alles and Gray (2016), accounting firms have been comfortable operating for many years by analyzing samples of accounting data and completing standard audit procedures using traditional auditing techniques. However, currently, both practitioners and academics have emphasized the use of analytics in the auditing area (Kend & Nguyen, 2020; PricewaterhouseCoopers [PWC], 2012; Wang & Cuthbertson, 2014; Cao, Chychyla, & Stewart, 2015). The American Institute of Certified Public Accountants(AICPA) defined audit analytics as "the science and art of discovering and analyzing patterns, identifying anomalies, and extracting other useful information in data underlying or related to the subject matter of an audit through analysis, modeling, and visualization of planning or performing the audit" (AICPA, 2017). The capability of big data analytics could allow auditors to improve their work by:

1) checking entire sets of data rather than just samples;
2) assisting risk assessment by identifying anomalies and trends, possibly by comparison to industry data, and directing auditors to items that need further investigation;
3) producing audit evidence through a thorough examination of a company's general ledger system.

On the basis of the foregoing ideas and arguments, this paper aims to further emphasize the importance, hindrances, recommendations, and practitioners' views on big data analytics from the auditing perspective. The remainder of the paper is structured in the following manner. To begin, in Section 2, we discuss the use of big data analytics in detecting and preventing fraud. Following this explanation, Section 3 presents the methodology used in this paper, and Sections 4 and 5 explain the advantages of incorporating big data analytics into audit practice and barriers to integrating big data analytics into audit practice, respectively. Section 6 provides some recommendations on how to improve the use of data analytics in detecting and preventing fraud. Finally, Section 7 concludes this paper by providing some insights from the related studies that have been carried out on the auditors and management team, i.e., Chief Executive Officers (CEOs) and Chief Financial Officers (CFOs) that highlight the current and future needs of big data analytics technology.

## 2. LITERATURE REVIEW

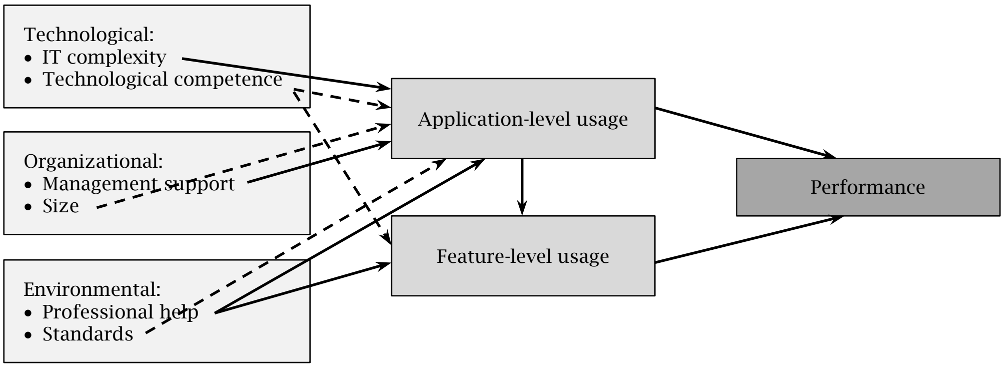
Auditors can use advancements in data analytics to undertake more effective audits. By examining data to detect patterns, correlations, and fluctuations statistics, audit data analytics approaches can be utilized in audit planning and procedures to identify and assess risk. Big data technologies can also assist auditors in gathering better evidence for their audit views and determining the root causes of restatements or fraud issues (Balios, Kotsilaras, Eriotis, & Vasiliou, 2020; Fay & Negangard, 2017). The paragraphs below provide some instances of how auditors use big data analytics in their audit job to discover and prevent fraud.

### 2.1. Technological, organizational, and environmental (TOE) framework

Li, Dai, Geshberg, and Vasarhelyi (2018) introduced the conceptual model of audit analytics usage and value based on the technological, organizational, and environmental (TOE) framework, as one of the ways auditors could use data analytics in audit work to detect and prevent fraud. The three aspects of the TOE framework are technological, organizational, and environmental. The technological element includes descriptive measures about the organization such as size or management attitude, as well as the organizational element, which includes descriptive measures about the organization such as size or management attitude, while the environmental element describes the environment in which a firm conducts business, including industry, competitors, and government relationships.

By adding the environmental context, which presents both limits and possibilities for technological adoption, the TOE framework (see Figure 1) gives more explanatory power. The left side of the framework depicts the antecedents of audit analytics use, such as factors that influence audit analytics use, while the right side of the model focuses on the performance and improvement of the internal audit process as a result of the technology's use. The application-level and feature-level usage of audit analytics can be separated. The extent to which auditors use audit analytics software in the audit process to detect and prevent fraud in a business is referred to as the application level of audit analytics utilization. When software that supports audit analytics is utilized often in the majority of audit processes, for example, application-level audit analytics utilization is deemed high.

**Figure 1.** TOE framework




*Source: Li, Dai, Geshberg, and Vasarhelyi (2018).*

Feature-level audit analytics utilization, on the other hand, is a composite measure that takes into account specific audit analytics methodologies as well as software features like summarization and regression, as well as the frequency with which they are used. It takes into account the number of different audit analytics techniques employed as well as the complexity of such approaches. To achieve a high degree of feature-level audit analytics usage, firm auditors must be familiar with both basic and advanced methodologies, as well as their strengths and shortcomings.

Auditors should also be able to use the most efficient ones to complete various audit jobs. It is conceivable for a company to increase application-level utilization while keeping feature-level consumption low. Auditors, for example, may routinely use basic audit analytics during the audit process but lack the knowledge and experience to apply more complex techniques. Furthermore, it is hypothesized that technological competence, IT complexity, firm size, management support, standards, and expert assistance will all have an impact on audit analytics utilization at the application level.

Furthermore, feature-level utilization is positively influenced by application-level usage, expert assistance, and technological proficiency. Internal audit performance is improved by using audit analytics at both the application and feature levels, indicating that technological competence, management support, and standards are positively associated with application-level audit analytics usage, while application-level usage, professional help, and technological competence have positive impacts on feature-level usage. The audit process is improved by using both the application and the features.

### 2.2. Data mining process

One of the most important areas in the database system is text data mining, which is one of the most exciting and promising developments in the informatics sector (Cardoni, Kiseleva, & De Luca, 2020; Banarescu, 2015). The data mining method is an analytical tool that is used to examine data and extract information from data sets in order to uncover patterns and relationships. Data mining is a frequently utilized technique in fraud detection systems for evaluating data patterns (Mohammadi, Yazdani, Khanmohammadi, & Maham, 2020). In today's world, fraud detection and prevention are critical in order to maintain a system safe from unauthorized access. Because information is mostly available in text format, data-text analysis, also known as exploitation of data such as text or text mining, refers to the process of extracting knowledge and information from documents of an organization. To complete the data mining, four tasks must be completed:

1) *Classification:* This is a method of dividing data into preset categories.

2) *Clustering:* Clustering is an unsupervised learning method that groups patterns of similar types together.

3) *Regression:* This is a process in which a method is developed to model data with the least amount of error.

4) *Association rule:* This rule is used to determine the frequency with which a pattern appears.

### 2.3. Geospatial analysis

Another way auditors use data analytics to prevent and detect audits is through geospatial analysis (Al-Marzooqi, 2021; Rezaee & Wang, 2019). Geospatial analysis is a type of visual analysis that is useful for determining and discovering fraud trends, as well as for comprehending the significance of the area where events occurred. By thoroughly scrutinizing data, visual analytics allows for a proactive response to threats and hazards. Auditors, for example, can go through thousands of insurance fraud claims to find clusters of interconnected parties. Auditors can also look at months of burglary reports to see if there is a trend that leads back to a suspect. Analytical instruments enable an organization's data to be identified, explored, indexed, and processed.

The application of automated processes and tools remains the most difficult task. It is critical to examine the prospects for expanding and integrating new models and computerized systems in preventing and detecting fraudulent acts as well as supporting deliberate managerial judgments. The method of getting data from a range of sources, since most of them have distinct formats, is critical to the successful deployment of an antifraud analytical system. It is suggested that the data obtained be analyzed in the same way, using the same procedures and methodology, in order to create homogeneous databases.

### 2.4. Computer-assisted audit techniques (CAATs)

The effectiveness and efficiency of auditing procedures in detecting and preventing fraud may be improved through the use of computer-assisted audit techniques, CAATs (Samagaio & Diogo, 2022). According to International Standard on Auditing (ISA) 401 "*Auditing in a Computer Information Systems Environment*", which discusses some of the uses of CAATs in the absence of input documents or lack of visible audit trail, CAATs enable auditors to download a client's data file and undertake complex operations including data selection and reasonableness testing.

CAATs are typically employed by large auditing firms for their large clients, and they can assist in the evaluation of controls by retrieving and analyzing pertinent data. It is a prevalent misperception among small audit teams that CAATs are a nice-to-have or that they can only be used effectively by large audit teams and businesses. However, with only a basic understanding of Excel and Word, a few easy tips and tactics, and a well-defined approach, huge rewards such as enhanced productivity, accuracy, and a deeper relationship with the business may not be that far away.

Audit software and test data are two examples of CAATs. First, audit software is a computer program that is used during substantive testing to verify the dependability of accounting controls and the integrity of computerized accounting records. It is used for auditing purposes to check the contents of the client's file. Calculation checks, finding system violations, detecting inappropriate items, selecting items for audit testing, and completeness checks are examples of typical testing carried out by auditors. Second, test data is information that the auditor uses to verify the operation of the company's computer software. The auditor generally uses test data to evaluate the entity's computer programs' application controls. The auditor, for example, prepares a set of simulated data that includes both valid and erroneous data. Valid data should be handled correctly, while faulty data should be flagged as an error. The outcomes are compared to the auditor's predicted outcome.

## 3. METHODOLOGY

This paper's methodology entails conducting a library search and evaluating prior literature reviews on the subject of big data analytics and the auditing profession. The library search spans a range of items, from online and print sources to articles in journals and chapters in books. Online databases such as Web of Science, Scopus, Science Direct, and Google Scholar are used to compile the references. References are drawn exclusively from journal articles, book chapters, and full-text documents published between 2011 and 2022.

## 4. ADVANTAGES OF INCORPORATING BIG DATA ANALYTICS INTO AUDIT PRACTICE

Big data allows for population-based audits due to its vast volume and real-time foundation (Richins, Stapleton, Stratopoulos, & Wong, 2017). This is likely its most important contribution: if any analysis (e.g., ratio, trend, comparison) can be performed on a population level, there is very little opportunity for risks and errors. The following are some of the advantages of applying big data analytics to auditing.

### 4.1. Greater number of transactions

Data analytics allows auditors to examine a larger number of transactions than they now do, boosting audits by increasing the amount of audit evidence available. Data analytics enables auditors to automate transaction testing, allowing them to test 100% of the population. According to Dagilienė and Klovienė (2019) as well as Liddy (2014), auditors will be able to evaluate 100% of clients' transactions in the future because of high-powered analytics. Auditors will be able to sort, filter, and analyze tens to millions of transactions to find any anomalies where the data does not meet the auditor's expectations, making it easier for auditors to focus on one area of possible concern and drill down on those items that pose the greatest risk.

### 4.2. Improved fraud detection in audits

Data analytics has promise for fraud detection since software tools allow auditors to quickly analyze enormous amounts of data and information. As a result, changing all upstream non-financial activities to cover up financial statement fraud is challenging. Fraud accounts for a relatively small fraction of transactions, and it is easy to overlook it in the small samples that auditors often examine. Analyzing all data with data analytics enhances the chances of finding red flags and dangerous outliers (Cao et al., 2015).

### 4.3. Develop more predictive models of going concern

Auditors have been under criticism recently for failing to offer going concern opinions for corporations that fell during the current financial crisis, such as Bear Stearns (Alles & Gray, 2016). Another possible component in increasing auditor assessments of client risk could be the use of big data analytics. In auditing, data analytics refers to the possibility of using non-financial and external data to better assist audit planning, notably in analyzing an organization's risk and more successfully auditing areas that need judgment, such as valuation or going concern. Furthermore, auditors can create models that forecast future events, which is known as predictive analytics. Auditors would be better positioned to assist their clients in making strategic business decisions.

## 5. BARRIERS TO INTEGRATING BIG DATA ANALYTICS INTO AUDIT PRACTICE

### 5.1. Data overload

The term "information overload" refers to getting an excessive amount of data (Mahdi et al., 2020). Decision-makers have a limited ability to process huge amounts of data, and existing research on people's ability to synthesize information from different sources regularly shows less than desirable results. The consequences of information overload are that a significant volume of accounting data can lead to inefficient financial and auditing decisions.

Though data analytic techniques make it feasible to extract vast amounts of data, auditors may have difficulty analyzing and interpreting the results because the output still generates an irresistible amount of data (Issa & Kogan, 2014). Auditors, for example, can use sophisticated analytic and data mining software to acquire and aggregate massive volumes of data from different sources. Yet, in order for data mining to be a useful analytic tool, auditors must have a thorough understanding of the data, its quality, and its relevance in order to form acceptable conclusions.

Furthermore, the results of data mining must be analyzed and evaluated in the context of the audit statements that are being verified. Although auditors are used to including non-financial data in their analyses, such as strategic systems auditing, the nature of big data analysis and the ensuing output could still result in lower audit quality owing to information overload. Excessive information can affect decision-making, making it less effective and efficient, leading to erroneous decisions, difficulties distinguishing relevant information, difficulties recognizing correlations between details and the overall perspective, disregard for large amounts of data, and increased decision-making time.

### 5.2. Data availability, relevance, and integrity

Increased information overload might make it difficult to effectively interpret key indications, which can lead to poor performance. As a result, one of the detrimental consequences of excessive information exposure is the inability to ignore irrelevant information. Increased amounts of irrelevant data diminish their overall decision-making performance. The diluting effect is a well-known phenomenon. To put it another way, a large amount of non-diagnostic data tends to confuse decision-makers and dilute or degrade the quality of their judgment. The dilution effect is particularly problematic in the auditing setting because auditors must determine which elements are most relevant for their audit conclusions from a vast amount of available data (Richins et al., 2017).

Paying attention to irrelevant data has the potential to drastically reduce the value gained from adding big data into the audit process. This is not, however, a challenge that only auditors face. Many businesses are overwhelmed by the amount of data available, and as a result, they are unsure how to extract value from it due to the unstructured nature of the data. Since non-financial information generated by big data is largely ambiguous and voluminous, audit firms will need to identify the types of information relevant to the audit process objectives, particularly non-financial information.

### 5.3. Pattern recognition

The ability to search for patterns in a vast population of data that would otherwise be invisible in samples or even smaller data sets is provided by big data (Alles & Vasarhelyi, 2014). In the auditing world, for example, spotting patterns in data such as complex data anomalies and inconsistencies that could indicate errors or fraud is a common part of the risk assessment process. Auditors have a tendency to focus on the wrong source of an error rather than combining data into patterns when making conclusions or judgments.

As a result, rather than examining combinations of discrepancies, auditors may be unable to identify fundamental errors on an account-by-account basis. Recent technological advances show that auditors can be trained to overcome pattern recognition challenges (Brown-Liburd, Issa, & Lombardi, 2015). Financial auditors will be better able to spot trends in data and more crucially, correctly interpret them if they have more contextual experience and training.

### 5.4. Ambiguity

The unstructured nature of data, which comes in a variety of formats such as text, image, and video, is another facet of big data that can lead to ambiguity in the organization's data and information. Auditors' understanding of the requirement for data management and processing software is complicated by unstructured data and information given as photographs, scanned documents, and transcribed inputs. Ambiguity can be caused by differences in the amount and type of information provided as well as source dependability and a lack of causal understanding of specific occurrences.

According to Brown-Liburd et al. (2015), predictive models in auditing can be used to simulate correlations among many significant aspects in ambiguous and highly subjective judgments such as a going concern and fraud. Auditors can capture linkages among various aspects by extracting transaction and historical data, as well as external data, to assess the risk that an entity will not continue as a going concern.

### 5.5. Lack of training and expertise of auditors

Auditors are being accused of not having or lacking the necessary training, skills, and ability to evaluate and comprehend big data in a company. Many businesses have established skills that have proven beneficial in dealing with traditional data, but they have not done so with big data, a new phenomenon

(Russom, 2011). In fact, sufficient training and skills are crucial for implementing analytical tools because they can have a significant impact on business performance, team morale, financial turnover, and the ability of the firm to attract and retain good people (Mcbride & Philippou, 2022). Employees should have a better grasp and competency in data analysis procedures for a company to be effective in harnessing the benefits of data analytic technologies.

## 6. WAYS TO IMPROVE DATA ANALYTICS PROCEDURES FOR PREVENTING AND DETECTING FRAUD

There are possible ways to improve data analytic procedures for preventing and detecting fraud. Among them are as follows: operational analysis, strategic analysis, and deep neural network.

### 6.1. Operational analysis

Operational analysis can be used efficiently and pleasantly in the near term by utilizing data and current information to comply with current actions for the most efficient identification and prevention of fraud. Data analysis, in its operational form, can be a tool for improving workplace conditions and reducing mental strain and manual procedures, particularly for processes that require the processing of large amounts of data and current information (Sun, 2012).

The main purpose of the operational analysis is to assist the anti-fraud manager in detecting and preventing any unlawful activities by examining the links between the possible fraudster, their characteristics such as direct or indirect subordination positions in the group hierarchy, relations, the movement of money, goods, or other valuables, methods of communication such as social networking, email, the modus operandi, and the sequence of events. The quality and range of data sources are critical to the success of such a strategy.

In the context of operational analysis, one of the goals of employing process analysis of data is to fill in information gaps or eliminate doubts and contradictions in an organization. Finally, the analytical product must be submitted in a clear manner, with at least one method of illicit operation or reasonable suspicion of fraud.

### 6.2. Strategic analysis

Dissimilar to operational analysis, strategic analysis takes a macro-level approach to prevent and detect fraud by looking at threats, vulnerabilities, risks, trends in the evolution of fraud phenomena, market evolution, economic development, and entity decline. It will scan both internal and external surroundings for vulnerabilities and institutional capacity, as well as opportunities and threats. A macro overview of fraud is provided by the strategic analysis.

### 6.3. Deep neural network

Deep learning, also known as a deep neural network, is an artificial intelligence system that analyses data using a deep hierarchical neural network to extract complicated and abstract properties underlying the raw data. Using deep learning is also a means to better and embrace textual data analytics in auditing. It is a sophisticated big data analytics tool that has been effectively deployed in a range of businesses (Valášková, Ward, & Svabova, 2021; Najafabadi et al., 2016). Furthermore, the use of deep learning in text analysis for auditing is still in its early stages. While artificial neural networks have been around since the 1950s, deep neural networks as a true artificial intelligence technique have only recently gained traction due to advances in computer power and data storage (Sun & Vasarhelyi, 2018).

Deep learning has been used by pioneers in this field, such as the Big 4 accounting companies, to leverage the power of textual big data to expose deeper insights and highlight risky areas. Deloitte, for example, uses Kira Systems 1's deep learning capabilities in conjunction with its business insights in cognitive technologies to execute document analysis tasks such as investigations, mergers, contract management, and leasing agreements.

Deep learning is an efficient and effective method for automatically extracting important metadata from semi-structured text data such as reports, earnings announcements, and emails due to the depth of the hidden layers in the deep neural networks. Thus, it can aid audit decision-making throughout all phases of the audit, including planning, internal control evaluation, substantive test, and conclusion.

## 7. CONCLUSION

The need for the auditors to utilize big data analytics in their working environment has been demanded nearly by a decade as the companies already emphasized this matter. A study of 2,000 CFOs and finance professionals conducted by Chartered Global Management Accountants (CGMA) in 2013 revealed that 87% of respondents agreed that big data will revolutionize the way business is done in the next ten years. Furthermore, according to a poll done by McKinsey Global Institute (as cited in Manyika et al., 2011), 51% of CEOs consider big data and analytics to be a top 10 organizational priority.

From the evidence collected from the literature search in this study, it is revealed that big data analytics make significant contributions to auditing since using big data as extra audit evidence makes it easier to discover abnormalities and predict fraud, which improves audit quality (Tang & Karim, 2017; Yoon, Hoogduin, & Zhang, 2015). Both external and internal auditors benefit from audit analytics. Furthermore, it provides auditors with new opportunities to examine potential risks, discover operational inefficiencies, and provide insights. Big data has a clear role to play in continuously improving fraud detection and establishing better analytical techniques. Data analysis as a tool for preventing and identifying fraud can be successfully employed in any industry, particularly in those where the data is or can be quickly translated into electronic format.

Furthermore, audit firms could form agreements with big data solutions companies to develop analytical tools that save money while enhancing results. This form of collaboration can save time and money by utilizing an already effective technology that has been proven to work in other sectors. As a result, auditors can spend less time designing and applying methodologies and tools to evaluate unstructured or structured data and more time performing assessments and evaluations of essential information collected from big data. However, the challenges that the auditors need to counter as highlighted in Earley (2015) are also worrying and require more specific measures to ensure that the advancement of technologies could eventually assist the auditors in preventing and detecting fraud from happening.

Therefore, more future studies are needed to confirm the level of auditors' understanding as well as the extend of data analytics usage in their working environment especially in the developing countries like Malaysia.

Finally, this study has limitations in that the findings may not be generalizable to other contexts, professions, or organizations. External auditors, in general, face some problems and implications as daily technology advances, and new obstacles emerge. As a result, it is critical for academicians, auditing professionals, and educational institutions to incorporate developments in the auditing profession. Based on the fact-findings from the literature on the current practices of big data analytics, external auditors must develop tools to improve their handling of big data and work to turn the abundance of evidence sources into a critical tool for exposing the risk of material misstatement and deception.

## REFERENCES


1. American Institute of Certified Public Accountants (AICPA). (2017, December 5). *Audit data analytics (ADAs) can transform audits: New AICPA guide will help auditors apply ADA techniques* [Press release]. Retrieved from https://www.aicpa.org/press/pressreleases/2017/audit-data-analytics-new-aicpa-guide-will-help-auditors-apply-ada-techniques.html
2. Alles, M., & Vasarhelyi, M. (2014). Developing a framework for the role of big data in auditing: A synthesis of the literature. Paper presented at the *37th Annual Congress of the European Accounting Association*. Retrieved from http://www.eaa2014.org/userfiles/FMKGHJL_EKFHMH_MQ1DP5AU.pdf
3. Alles, M., & Gray, G. L. (2016). Incorporating big data in audits: Identifying inhibitors and a research agenda to address those inhibitors. *International Journal of Accounting Information System, 22*, 44–59. https://doi.org/10.1016/j.accinf.2016.07.004
4. Al-Marzooqi, S. (2021). Promising technologies for future-proofing public sector audit work. *International Journal of Government Auditing, 48*(3), 52–53. Retrieved from https://intosaijournal.org/promising-technologies/
5. Balios, D., Kotsilaras, P., Eriotis, N., & Vasiliou, D. (2020). Big data, data analytics and external auditing. *Journal of Modern Accounting and Auditing, 16*(5), 211–219. https://doi.org/10.17265/1548-6583/2020.05.002
6. Banarescu, A. (2015). Detecting and preventing fraud with data analytics. *Procedia Economics and Finance, 32*, 1827–1836. https://doi.org/10.1016/S2212-5671(15)01485-9
7. Brown-Liburd, H. B., Issa, H., & Lombardi, D. (2015). Behavioral implications of big data's impact on audit judgement and decision making and future research directions. *Accounting Horizons, 29*(2), 451–468. https://doi.org/10.2308/acch-51023
8. Cao, M., Chychyla, R., & Stewart, T. (2015). Big data analytics in financial statement audits. *Accounting Horizon, 29*(2), 423–429. https://doi.org/10.2308/acch-51068
9. Cardoni, A., Kiseleva, E., & De Luca, F. (2020). Continuous auditing and data mining for strategic risk control and anticorruption: Creating "fair" value in the digital age. *Business Strategy and the Environment, 29*(8), 3072–3085. https://doi.org/10.1002/bse.2558
10. Chartered Global Management Accountants Report (CGMA). (2013, October 16). *From insight to impact: Unlocking opportunities in big data*. Retrieved from https://www.cgma.org/content/dam/cgma/resources/reports/downloadabledocuments/from-insight-to-impact-unlocking-the-opportunities-in-big-data.pdf
11. Dagilienė, L. & Klovienė, L. (2019). Motivation to use big data and big data analytics in external auditing. *Managerial Auditing Journal, 34*(7), 750–782. https://doi.org/10.1108/MAJ-01-2018-1773
12. Earley, C. E. (2015). Data analytics in auditing: Opportunities and challenges. *Business Horizons, 58*(5), 493–500. https://doi.org/10.1016/j.bushor.2015.05.002
13. Fay, R., & Negangard, E. M. (2017). Manual journey entry testing: Data analytics and the risk of fraud. *Journal of Accounting Education, 38*, 37–49. https://doi.org/10.1016/j.jaccedu.2016.12.004
14. Gartner. (2013). *Information technology glossary: Big data*. Retrieved from http://www.gartner.com/it-glossary/big-data
15. Gillis, T., & Stephanny, P. (2014). Going beyond the data: tax data is big data. *Tax Planning International: Indirect Taxes, 12*(9), 2–5. Retrieved from https://assets.kpmg/content/dam/kpmg/pdf/2015/03/going-beyond-the-data-artcile-2-tax-data-is-big-data.pdf
16. Hadi, H. J. A., Shnain, A. H., Hadishaheed, S., & Ahmad, A. H. (2015). Big data and the five v's characteristics. *International Journal of Advances in Electronics and Computer Science, 2*(1), 16–23. Retrieved from https://www.researchgate.net/publication/332230305_BIG_DATA_AND_FIVE_V%27S_CHARACTERISTICS
17. Issa, H., & Kogan, A. (2014). A predictive ordered logistic regression model as a tool of quality review of control risk assessments. *Journal of Information Systems, 28*(2), 209–229. https://doi.org/10.2308/isys-50808
18. Kend, M., & Nguyen, L. A. (2020). Big data analytics and other emerging technologies: The impact on the Australian audit and assurance profession. *Australian Accounting Review, 30*(4), 269–282. https://doi.org/10.1111/auar.12305
19. Kim, G., Trimi, S., & Chung, J. (2014). Big-data applications in the government sector. *Communications of the ACM, 57*(3), 78–85. https://doi.org/10.1145/2500873
20. Li, H., Dai, J., Geshberg, T., & Vasarhelyi, M. A. (2018). Understanding usage and value of audit analytics for internal auditors: An organizational approach. *International Journal of Accounting Information Systems, 28*, 59–76. https://doi.org/10.1016/j.accinf.2017.12.005

21. Liddy, J. (2014, August 4). The future of audit. *The Forbes.* Retrieved from https://www.forbes.com/sites/realspin/2014/08/04/the-future-of-audit/?sh=741b21e52725
22. Mahdi, M. N., Ahmad, A. R., Ismail, R., Subhi, M. A., Abdulrazzaq, M. M., & Qassim, Q. S. (2020). Information overload: The effects of large amounts of information. In *Proceeding of the 2020 1st Information Technology to Enhance E-learning and Other Application Conference [IT-ELA]* (pp. 154–159). Retrieved from https://ieeexplore.ieee.org/document/9253082
23. Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Hung Byers, A. (2011). *Big data: The next frontier for innovation, competition, and productivity.* Retrieved from https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/big-data-the-next-frontier-for-innovation
24. Mcbride, K., & Philippou, C. (2022). "Big results require big ambitions": Big data, data analytics and accounting in masters courses. *Accounting Research Journal, 35*(1), 71–100. https://doi.org/10.1108/ARJ-04-2020-0077
25. Mohammadi, M., Yazdani, S., Khanmohammadi, M., & Maham, K. (2020). Financial reporting fraud detection: An analysis of data mining algorithms. *International Journal of Finance and Managerial Accounting*, *4*(16), 1–12. Retrieved from https://cutt.ly/2KMpfRh
26. Najafabadi, M. M., Villanustre, F., Khoshgoftaar, T. M., Seliya, N., Wald, R., & Muharemagc, E. (2016). Deep learning techniques in big data analytics. In B. Furht, & F. Villanustre (Eds.), *Big data technologies and applications* (pp. 133–156). https://doi.org/10.1007/978-3-319-44550-2_5
27. Nielsen, M. (2015). *Neural networks and deep learning*. Retrieved from https://static.latexstudio.net/article/—2018/0912/neuralnetworksanddeeplearning.pdf
28. PricewaterhouseCoopers (PWC). (2012). *Data analytics: How data analytics can help internal audit better understand risk.* Retrieved from https://www.pwc.com/en_US/us/industry/utilities/publications/assets/pwc-utility-company-internal-audit-data-analytics.pdf
29. Rezaee, Z., & Wang, J. (2019). Relevance of big data to forensic accounting practice and education. *Managerial Auditing Journal, 34*(3), 268–288. https://doi.org/10.1108/MAJ-08-2017-1633
30. Richins, G., Stapleton, A., Stratopoulos, T. C., & Wong, C. (2017). Big data analytics: Opportunity or threat for the accounting profession? *Journal of Information Systems, 31*(3), 63–79. https://doi.org/10.2308/isys-51805
31. Russom, P. (2011). *Big data analytics* (TDWI best practices report (fourth quarter)). Retrieved from https://tdwi.org/research/2011/09/best-practices-report-q4-big-data-analytics.aspx
32. Samagaio, A., & Diogo, T. A. (2022). Effect of computer assisted audit tools on corporate sustainability. *Sustainability, 14*(2), 705. https://doi.org/10.3390/su14020705
33. Sun, H. (2012). Understanding user revisions when using information system features: Adaptive system use and triggers. *MIS Quarterly, 36*(2), 453–478. https://doi.org/10.2307/41703463
34. Sun, T., & Vasarhelyi, M. A. (2018). Embracing textual data analytics in auditing with deep learning. *The International Journal of Digital Accounting Research, 18*, 49–67. https://doi.org/10.4192/1577-8517-V18_3
35. Tang, J., & Karim, K. (2017). *Big data in business analytics: Implications for the audit profession.* Retrieved from https://www.cpajournal.com/2017/06/26/big-data-business-analytics-implications-audit-profession/
36. Valášková, K., Ward, P., & Svabova, L. (2021). Deep learning-assisted smart process planning, cognitive automation, and industrial big data analytics in sustainable cyber-physical production systems. *Journal of Self-Governance and Management Economics, 9*(2), 9–20. https://doi.org/10.22381/jsme9220211
37. Wang, T., & Cuthbertson, R. (2014). Eight issues on audit data analytics we would like researched. *Journal of Information Systems, 29*(1), 155–162. https://doi.org/10.2308/isys-50955
38. Yoon, K., Hoogduin, L., & Zhang, L. (2015). Big data as complementary audit evidence. *Accounting Horizons, 29*(2), 431–438. https://doi.org/10.2308/acch-51076