

AUDIT DATA ANALYTICS: A Game Changer for Audit Firms

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Article History

Received : 18 July 2022; Revised : 23 September 2022; Accepted : 30 November 2022;

Published : 01 February 2023

Abstract: The objective of this article is to shed light on the emergence of recent auditing technology i.e. integrating data analytics into auditing procedures. The reliance on digitalization as well as the increasing volume of data accessibility has reckoned the importance of using Big data and Data Analytics (BDA) in audit work. Therefore, an attempt is made in this article to analyze the possible upshots of big data on audit procedures. The article contributes to auditing literature by discussing in-depth the usage of audit data analytics and the challenges that are likely to be confronted both by the auditors and the client process.

Keywords: Big data, Audit Data Analytics, Auditing.

1. INTRODUCTION

In recent decades, the auditing sector has received much interest, especially after World Com, Enron, and other accounting scandals (Alles, 2015). An audit comprises looking for patterns in a company's financial and non-financial data. Regulations are being reexamined in order to ensure that audit systems and processes are properly led in acquiring sufficient information. The auditors' professional judgment is used to support this strategy (Adrian & Viorica, 2015). According to existing audit literature, audit firms generally improve the social importance of auditing and the quality of auditing functions by making methodological improvements aimed at regaining the public image of audit quality (Curtis & Turley, 2007; Robson *et al.*, 2007; Power, 2003). Our

To cite this paper:

Siriya Kanthi Herath & Prem Lal Joshi (2023). Audit Data Analytics: A Game Changer for Audit Firms. *International Journal of Auditing and Accounting Studies*. 5(1), 29-48. [https://DOI: 10.47509/IJAAS.2023.v05i01.02](https://doi.org/10.47509/IJAAS.2023.v05i01.02)

research focuses on incorporating the latest episodes in the evolution of audit technology: data analytics into the auditing process. This has become a game-changer for audit firms.

Big data and Data Analytics (BDA) have recently become very popular because of the rising dependence on digital and automation, as well as the increasing volumes of data available. Big data analytics has become a common occurrence in today's culture, and it is a touchy subject in the auditing field. The term "big data" is usually used to describe a collection of information that is large. Audit assignments include planning the audit, performing the client risk assessment, acquiring evidence, conveying information to appropriate personnel, and running internal control tests at various phases of the audit process (Appelbaum *et al.*, 2017). Many companies are increasing their investments in the storage and handling of enormous volumes of data in various formats, and this trend is expected to continue (Cao *et al.*, 2015). This study adds to the auditing literature in a substantial and timely way, providing critical information to researchers working to expand knowledge in the auditing field.

Auditor duties will unavoidably evolve as a result of both big data and big data analytics. The effect of big data on audits is investigated in this article. Auditors must perform critical analyses of accounting data in addition to typical auditing procedures. As a result, auditors' procedures and processes will also need to alter in order to deliver expert judgments.

The rest of this article is divided into sections by the headings listed below. The article's second section introduces big data and decision-making based on data. Based on different study findings, the third section investigates the nature and influence of audit analytics on auditing. The fourth section delves into the basics of audit analytics. The fifth section is dedicated to a study of audit analytics' challenges and issues. The study finishes with some audit data analytics observations.

2. DATA-DRIVEN DECISION MAKING AND BIG DATA

Although the term "big data" was seldom ever used in the early 1990s, it has since become widely accepted. Big data and data-driven decision-making are now viewed by many firms as essential to a company's success. Similar to how decision-making in auditing and accounting is becoming more dependent on access to data, big data is now seen as crucial to a company's auditing and accounting data strategy. Many auditing firms are currently exploring new skills in their quest to become data-driven. It is not really simple to change a firm's decision-making process, yet doing so will have the biggest transformative

influence on the performance of audit firms. In order to provide better service to their customers and consumers, firms can examine and analyze their data utilizing a data-driven strategy. Data-driven decision-making presents the auditing industry with a number of issues despite the fact that data sources are very heterogeneous, accessible at different scales, and comprise a mixture of organized and unstructured data. A discussion of big data and data-driven decision-making is presented next.

2.1. Big Data

Our study begins with an introduction to the key ideas of big data and data-driven decision-making. According to Gartner (2012), “big data” is “high-volume, high-velocity, and high-variety information assets that necessitate innovative time and cost-effective data processing methodologies that result in improved insight, decision-making capabilities, and process automation.” Big data, as defined by (Owais & Hussein, 2016), is a category of data that has undergone systematic analysis and is dependent on the availability of advanced technology, processes, and resources. The term “big data” is frequently used interchangeably with “data analysis.” Many characteristics or attributes that are listed by nV’s characteristics are present in big data. “Big data” is a word used to describe a large amount of information from several sources which can be grouped into five classifications: velocity, volume, value, variety and veracity (Favaretto *et al.*, 2020; Elgendy & Elragal, 2014). The five Vs that are generally used to define big data have been joined in recent years by variability and visualization, giving us a total of seven Vs (Figure 1).

Volume refers to how much and how big data an organization manages and analyzes. To put it another way, the data’s magnitude is its size. Volume denotes a vast amount of data, although there is no agreement on what constitutes “big.” The definition of “big data” varies depending on who is using it. For a multinational corporation, the amount of data that is considered “Big” for a small business may be irrelevant (Balios, *et al.*, 2020a; Vasarhelyi, Kogan, & Tuttle, 2015). Whether certain data are enormous is judged by whether or not they exceed the capacity of the information systems that operate with them (Vasarhelyi *et al.*, 2015).

Variety refers to data that is structured, semi-structured, or unstructured (Elgendy, Elragal & Päivärinta, 2021) as a result of various sources of data generated by humans or robots. Big data isn’t always homogeneous. The most pressing issue for auditors is veracity, which refers to the extent to which Big Data provides correct information (Yoon, Hoogduin, and Zhang (2015) and

data integrity (Alles & Gray, 2015). The quantity denotes the total amount of data, while the variety denotes whether the material is structured or unstructured. The strategic and informative benefits of big data are referred to as value (Elgendy, Elragal & Päivärinta, 2021). The value or utility of big data comes from the discovery of insights and patterns that contribute to much more efficient operations, stronger customer relations, and other quantitative and provable financial benefits.

The velocity refers to how rapidly you can get the data. Velocity refers to the rate at which businesses acquire, store, and analyze data, such as the number of digital posts or web searches they receive in a given day, hour, or another timeframe. The “truth” or reliability of information and data assets, which is usually the decisive element in executive confidence, is referred to as veracity. Veracity also means trustworthiness and reputation of data. Variability refers to how findings change over time as the analysis of the data changes or as new data is added to the mix (Elgendy, Elragal & Päivärinta, 2021). The dynamic aspect of data is represented through variability. Visualization is the portrayal of data in meaningful ways, as well as hidden patterns and trends (Mikalef *et al.*, 2018). According to Earley, aesthetically appealing metrics impress clients (2015).

Arguments abound over Big Data’s properties. Big data attributes have been categorized into up to 42 Vs by different academics. For instance, it might be 9 Vs. (Owais & Hussein, 2016), 10 Vs. (Khan *et al.*, 2018), 17 Vs. (Panimalar *et al.*, 2017), and 42 Vs (Shafer, 2017). The most important Vs are Volume, Variety, Velocity, Veracity, Value, Validity, Variability, Volatility, and Visualization. Owais & Hussein (2016) described 9 V’s traits using a set of V’s traits of the Big Data that were gathered from numerous research studies. The nine Vs are commonly referred to as the 9Vs: Validity, Veracity, Velocity, Volume, Variability, Volatility, Visualization, and Value (Figure 4). As a result, big data also has the additional characteristics of validity and volatility. Validity is an important aspect to consider when assessing the veracity of big data because the data must be reliable and proper for the intended usage. In order to make the right decisions, you need data that is evidently valid. The process of ensuring that unaltered data has been transferred is known as data validation. Data volatility measures how quickly data disappears from a system, making it a key factor in assessing the likelihood of obtaining the most useful evidence. Using a volatility model, an investigator can determine the likelihood that the evidence is present. As shown in Figure 4, Owais & Hussein (2016) divided these nine Big Data attributes into five CPIVW categories. These are:

collecting evidence, processing data, ensuring data integrity, visualizing data, and valuing data.

Because of its great volume, variety, velocity, value, and veracity, big data cannot be managed using traditional methods and approaches (Elgendy & Elragal, 2014). Traditional technologies are unable to address the scale, flexibility, and accessibility concerns that big data demands (Saggi & Jain, 2018). This is because big data encompasses not just the ability to manage massive amounts of data, but also a diverse set of advanced analytics and economic opportunities (Elgendy, Elragal & Päivärinta, 2021). It enables real-time automated tasks as well as intraday decision-making. As a result, novel processing methods are needed to obtain insight, improve decision-making, and streamline procedures (Mikalef *et al.*, 2018). According to Gartner (2012), to be meaningful and useful for decision-making, massive data must be reviewed or processed in unique ways. Furthermore, data comes from a number of channels and technologies, and the velocity and quantity of data created within organizations fluctuate significantly, necessitating the use of analytics to improve functional agility and flexibility (Elgendy, Elragal, & Päivärinta, 2021). To expose in-depth information for judgments, high velocity, high volume, and high variety data must be handled with advanced technologies including analytics and algorithms.

As mentioned earlier, Big Data is altering the foundation of business measurement and assurance (Alles, 2015; Vasarhelyi, Kogan, & Tuttle, 2015). Big data is an additional source of data for the audit function, as per Yoon, Hoogduin, and Zhang (2015), and its utility should be assessed using audit evidence sufficiency, integrity, and relevance principles. Moffitt and Vasarhelyi (2013) also believe that big data can be used to create new types of audit evidence. Some scholars explore Big Data from two perspectives: on the one hand, the elements of Big Data, and the dimension and features of enormous data on the other (Alles & Gray, 2015).

As technology progresses, nearly any type of data may now be captured, stored, and evaluated very fast (Cao, Chychyla, and Stewart, 2015). Furthermore, the growing integration of machine learning supported systems and human decision-makers in organizations has sparked interest in synergic augmenting their intellectual ability and capabilities, resulting in more “intelligent” data analysis and, as a result, continuing to support and improve decision making (Grover *et al.*, 2020; Kotsiantis *et al.*, 2006). Depending on the setting and the type of choice, this partnership has resulted in multiple dimensions of intelligence and a spectrum of applications ranging from simple

to complicated, with the goal of best merging human-artificial capabilities for improved data-driven making decisions (Trunk, Birkel, & Hartmann (2020). Continuous auditing has become incredibly popular for allowing automatic and real-time analysis due to the large amount and quick velocity of these data (Vasarhelyi, Alles, & Williams, 2010). Auditors, however, face a hurdle in filtering vast amounts of data in order to acquire useful and comprehensible data for auditing purposes (Brown-liburd & Vasarhelyi, 2015).

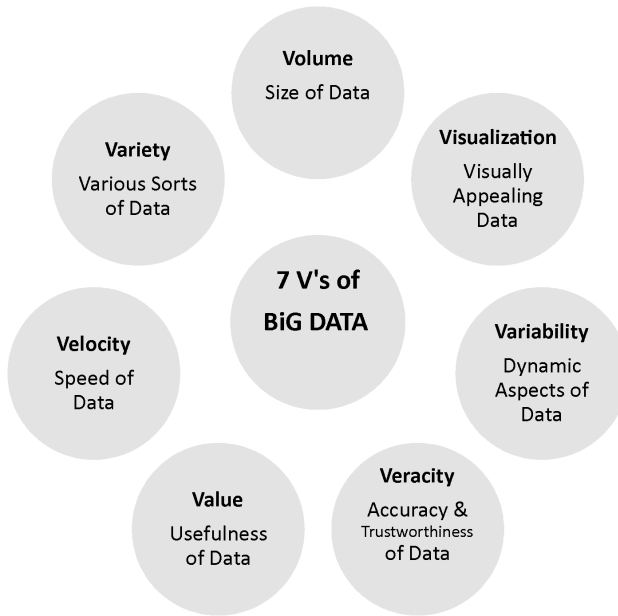


Figure 1: Seven Vs of Big Data

2.2. Decision-Making Based on Data

The act of acquiring, analyzing, assessing, and comprehending data in order to make intelligent judgments is known as data-driven decision-making, and it is frequently performed through the use of analytics or deep learning methodologies and programming approaches (Mandinach, 2012). In the mid-twentieth century, researchers began to study decision systems, which encompassed both human and machine decisions, with strong predictive ability. This prompted a renewed focus on decision systems, including the people, procedures, technologies, and data which are used to generate or inform decisions (Power, Heavin, *et al.*, 2019). Furthermore, data-driven decision-making has gotten a lot of attention because of advances in data science, machine learning, big

data, and analytics (Elgendy, Elragal & Päivärinta, 2021). As a result, data-driven judgment is now widely accepted as a strategy for generating stronger, high-quality recommendations by incorporating decision-makers’ insight and talent with data analysis, leading to more logical conclusions and better results (Elgendy, Elragal, & Päivärinta, 2021).

Massive data require a paradigm shift from traditional information analysis, as a result of their complexity (Grover & Kar, 2017). Therefore, big data is widely considered something that goes beyond traditional data and necessitates a new way of storing, managing and processing data. Numerous methods and analytical methodologies are used in numerous industries, which have attracted attention in academic studies since they provide improved decision-making since they can integrate and evaluate a variety of data, s such as Facebook data, etc., (Elgendy, Elragal & Päivärinta, 2021). With the use of analytical tools and input from a variety of information sources, more cooperative decision-making processes have been enabled (Rathore, Kar & Ilavarasan, 2017).

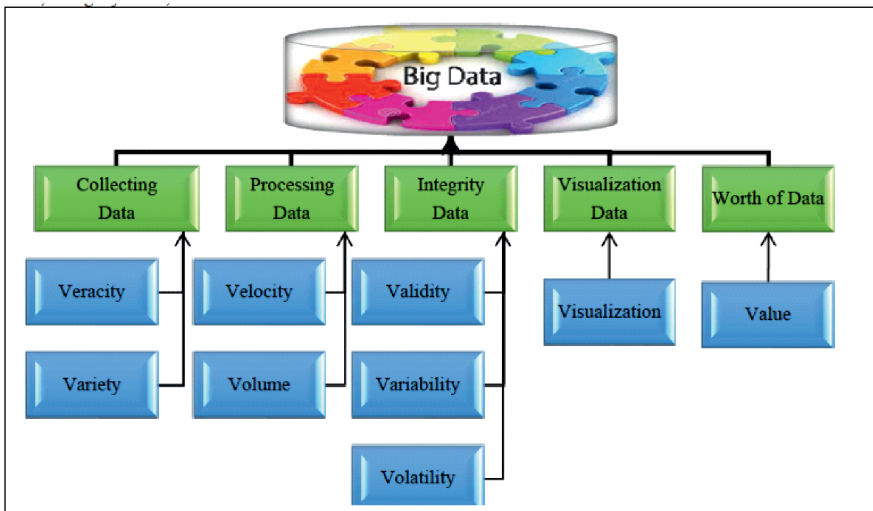


Figure 2: Five Categories CPIVW of the Big Data with their 9 V’s Characteristics

Source: Owais & Hussein, 2016, p. 255

As a result, corporate decision-making has become more reliant on technology, which has advanced from facilitating human decision-makers to totally automating decision-making operations (Elgendy, Elragal, & Päivärinta, 2021). Some researchers, however, highlight that notwithstanding the increasing amount of data, technologies, and ideas accessible, decision-makers continue to underutilize the power of contemporary technology, particularly

in the absence of well-defined rules and processes that necessitate thorough investigation (Power, Cyphert, & Roth, 2019; Grover *et al.*, 2020). The next part contains some practical considerations about audit data analytics.

3. BIG DATA ANALYTICS (BDA) AND AUDITING

Big Data Analytics (BDA) is a thorough method for obtaining, organizing, and analyzing massive data sets that use sophisticated analytics techniques. BDA, according to Saggi and Jain (2018), is a technology-driven ecosystem that aids in extracting knowledge from data in an understandable and relevant manner, resulting in improved decisions and informed decisions. The goal of BDA is to use technology and scientific techniques to monitor operations, analyze performance and provide financial information in much more meaningful ways (Blix, Edmonds, & Sorensen, 2021). Furthermore, it can boost operational efficiency by allowing real-time decision-making, improving the quality of the data and diagnosticity, and resulting in better judgment (Jha, Agi, & Ngai (2020).

Data analysis is commonly associated with the term “big data.” As Earley (2015) cited “according to Alles and Gray (2014), big data is generally defined in accounting research by the types of analysis, which are able to be carried out using the data, including Data Analytics or predictive analytics, instead of by the type of information source”.

The growing use of internet-based social networks has revolutionized both consumer and corporate behavior. To stay competitive, modern firms and organizations are eager to adopt cloud and Internet sources of data, including social media (Balios, 2020b). Advanced analytical technologies are also used to help business specialists make efficient plan implementation decisions. Accounting information may be processed, tracked, and audited online, potentially cutting accounting and tax time in half (Horak & Boksova, 2017). Processing large amounts of video, sound, and textual data can help with accounting and auditing activities (Crawley & Wahlen, 2014; Warren, Moffitt, & Byrnes, 2015).

The audit role of public accounting companies approaches data analytics in a different way than the advisory function. The focus is on improving the efficiency and effectiveness of audits, rather than on innovating and competing on aesthetically appealing analytics to wow clients (Earley (2015). The audit function has been slower to implement BDA than other professions such as counseling or forensic examination (Katz, 2014; Whitehouse, 2014). Given the potential for litigation and, as a result, the stringent regulatory auditing environment, it is reasonable that firms would be wary of seeking BDA within

the audit profession. Nonetheless, BDA is being heralded as the auditing technology of the future (Liddy, 2014; Lombardi, Bloch, & Vasarhelyi, 2014).

Furthermore, these and many other anticipated measures and methodologies of predictive auditing are applied to measurement assurance (Vasarhelyi and Kuenkaikaew 2013). According to Alles (2015), auditing lags behind management's usage of technology. Alles (2015) expresses concerns about professionals' readiness to adopt new technology, such as the application of large data. The rapid creation of audit database systems by internal audit departments, as well as enormous amounts of client data created and held by audit firms, are unique to audit.

The audit value chain (Yoon, Hoogduin, & Zhang, 2015) will, on the other hand, give more types of audit information, much before the primary documentation of a business transaction and often in parallel with the normal stream of evidence. According to Capriotti (2014), BDA has the potential to be the most significant change in auditing methodology and programming techniques since the advent of techniques and programming strategies for automated audits.

Utilizing problem-driven data analytical approaches to big data, auditors will be able to update their traditional substantive procedures, tests of controls, and analytical tests in the context of an auditing process (Titera, 2013). Auditors must audit companies that employ big data and data analytics in their operations. As a result, auditors must adapt to the changing environment and use powerful predictive and prescriptive analytics (Appelbaum, Kogan, & Vasarhelyi, 2017).

Big data is projected to provide significant financial benefits to auditors and audit clients (Salijeni, 2019). Richins *et al.* (2017) also highlighted that auditing firms should use Big data proactively in auditing procedures, to reap the benefits of its potential benefits. The relevance and integrity of data that changes rapidly are referred to as veracity (Vasarhelyi *et al.*, 2015; Zhang *et al.*, 2015; Yoon, Hoogduin, and Zhang (2015).

The accountancy profession has faced both possibilities and challenges because of Big Data which refers to the integration of finance, technology, and information (Balios, *et al.*, 2020a). As a result, accountants' function as consultants and their ability to think strategically, helping management decision-making, are changing. Big data has tightened and improved the relationship between the management and management accountants. Management accountants to find process can use additional analytical tools and product improvements while saving money.

According to Frey and Osborne (2013), there is a 94 percent chance that accounting and auditing positions will be automated in the future, based on task characteristics. While Frey and Osborne (2013) argue that accounting and auditing are vulnerable to automation due to a lack of machine inimitable abilities, Richins *et al.*, (2017) argue that accountants have the ability to think strategically and use their business knowledge to supplement the value supplied by big data analytics.

Researchers have examined various aspects of big data in auditing: the consequences of consumers' growing use of big data (Appelbaum, & Vasarhelyi, 2017) and the sources of useful big data for auditing (Vasarhelyi, Kogan, & Tuttle, 2015; Zhang, Hu, *et al.*, 2015); Gepp *et al.*, (2018) emphasis on the utility of modern big data approaches in auditing. For example, Gepp *et al.* (2018) looked at the questions posed by Appelbaum *et al.* (2017) and Vasarhelyi *et al.* (2015) about the use of big data in auditing; "What models may be used?" Which of these options appear to be the most likely to succeed?" and "What will the prioritization algorithms be?" Rose *et al.* (2017) investigated how the timing of assessing analytical results from big data technologies affects the use of professional judgment and the ability of auditors to make decisions. Gepp *et al.*, (2018) focused on the use of modern big data methodologies in auditing. Gepp *et al.*, (2018) discovered that they are less common than in other fields, although some academics think that using BDA to ensure audit quality is useful and valuable (Vasarhelyi *et al.*, 2015).

Brown-Liburd *et al.* (2015) looked into the behavioral effects of big data on auditor assessment, namely data overload, relevancy, pattern matching, and ambiguity. They concluded that incorporating big data approaches into the auditing toolkit would be beneficial. Brown-Liburd *et al.*, (2015) also emphasized the need of using the technique and data collection that are most relevant for each situation, indicating the need for future research in this area. Accounting and auditing tasks can benefit from big data video, audio, and textual information processing (Crawley & Wahlen, 2014; Warren, Moffitt, & Byrnes, 2015).

Organizational aspirations to use Big Data and Big Data Analytics (BDA) in external audits are investigated by Dagiliene and Kloviene (2019). Their study adds to the modest body of work by conducting an empirical assessment of the current condition of BDA utilization and driving external auditing. To describe how numerous variables influence BDA use, Dagiliene and Kloviene (2019) used a contingency-based conceptual framework as a model. In the framework of auditing, the writers investigate the phenomenon of BD

and BDA. It is vital to note that BD has distinct properties as compared to traditional data, and the ability to use big data is becoming highly relevant for audit firms, which is new to auditors' understanding.

Big Data (BD) technology has gained momentum across a broad array of industries in recent years, from government and business to science and research. (Ajana, 2015; Dagiliene & Kloviene, 2019). Businesses are confronted with an enormous amount of semi-structured and disorganized big data, which they would use and manage in order to stay creative, effective, and competitive. Accounting and auditing are not any different (Dagiliene & Kloviene, 2019).

According to Wang and Cuthbertson, the prospective significance of BD and Big Data Analytics (BDA) for innovative auditing techniques is obvious (2015). Several studies have looked into and investigated wide areas of big data analytics in auditing, explaining and contextualizing the issues, and drawing attention to them among researchers (Alles, 2015; Brown-Liburd, Issa, & Lombardi, 2015; Earley, 2015; Wang & Cuthbertson, 2015; Alles & Gray, 2016; Connelly *et al.*, 2016; Arnaboldi *et al.*, 2017; Dagiliene & Kloviene, 2019).

The use of big data and data analytics in auditing ensures audit quality and fraud detection. Employee participation is reduced thanks to improved information, new technology, and business automation systems. Accounting knowledge and abilities must always be linked to big data and data analytics, and modern auditors must learn about data and tools to establish an analytics perspective. It is critical to emphasize that when compared to other types of data, BD has unique qualities, and the capacity to use BD within BDA is now becoming increasingly relevant for audit companies, which is new to the authors' knowledge. Organizations are encouraged to modify their techniques as technology develops, surprising people who are not anticipating it. Companies alter their operational strategies and procedures. New risks and possibilities must be considered. In an increasingly data-driven environment, auditors must be prepared to respond to technological changes. Using BDA in the audit brings tremendous opportunities for organizations as well as substantial problems as discussed in a later section.

Big data, as defined by the literature, goes beyond traditional data and needs different storage, management, and processing methods than previously available data and information. Big data is also commonly considered to have a direct and positive impact on accounting and auditing, enabling its inclusion in modern research worthwhile. The subsections that follow provide some discussions about audit data analytics and the challenges faced by auditors and client firms.

4. AUDIT DATA ANALYTICS (ADA)

Audit data analytics is defined as follows, according to the American Institute of Certified Public Accountants (AICPA, 2015):

“Audit data analytics (ADA) is 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 for the purpose of planning or performing the audit” (p. 92).

Analysts should spend less time on mundane tasks like collecting evidence and more effort on activities like investigating outliers, modifying business procedures, making judgments, and reporting results, which are all likely perceived as making a contribution to the audit engagement by the client (Forbes, 2015; PwC, 2015). According to Bierwirth (2019), “data analytics” and “big data” are becoming game-changer for auditors as firms look for ways to provide more value to clients while responding to new legislation and increasing stakeholder demands. The future of the auditing sector is being hailed as data analytics (Lombardi, Bloch, & Vasarhelyi, 2014; Liddy, 2014). Furthermore, it is the potential to be the most important transformation in auditing since the advent of paperless audit tools and technology, according to Capriotti (2014).

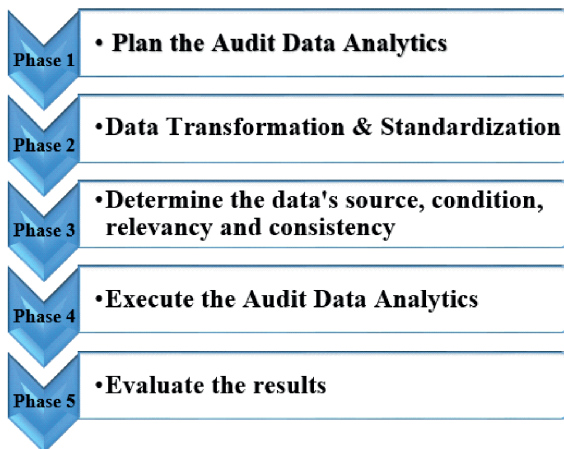
Accountants’ and auditors’ jobs will unavoidably change because of big data analytics, and financial accountants should go beyond record keeping to give crucial data to decision-makers (Shimamoto, 2020). Understanding and possibly initiating new data analysis (Holsapple *et al.*, 2014) could be beneficial since auditors evaluate business financial data, the majority of which will be generated by application areas and analytics incorporated in management enterprise systems. Audit analytics is the use of data, information systems, and analytics in auditing. As pointed out by (Blix, Edmonds, & Sorensen, 2021) (Blix, Edmonds, & Sorensen, 2021), with a growing reliance on automated technologies to generate data analysis reports, the auditing profession is changing.

AICPA (2017) had also released a new report titled “Guide to Audit Data Analytics (ADAs),” which is intended to provide financial statement auditors with an overview and introduction to data analytic technologies so that they can use them in their audit engagements. Audit data analytics (ADAs), according to the AICPA (2017) are strategies that assist auditors in using existing technologies and moving towards a data-driven approach to preparing or completing audits. Furthermore, AICPA has established five critical steps for employing audit

data analytics (Figure 2). These steps are: 1) Plan the Audit Data Analytics, which include determining what audit goals you want to achieve, what data you have, and what types of tests are necessary (analytical procedure, test of details substantive test, etc.), 2) Data Transformation & Standardization which include prepare or modify the structure of the data so that it is ready to utilize. 3) Determine the data's source, condition, and kind, as well as its relevance and consistency. 4) Execute the Audit Data Analytics, and 5) review the results to see if any additional steps are required to meet your objectives.

According to Kogan, Alles, Vasarhelyi, and Wu (2010), practical applications that allow for comprehensive data analysis rather than brief data analysis, as well as the incorporation of internal, external, and financial data, and the connection of audit procedures with environmental Big Data, alter the auditing process. Vasarhelyi, Kogan, & Tuttle (2015) claimed that companies have gradually widened the scope of their information management from conventional data processors to automatic data gathering in order to gain a competitive advantage, relying on automatic sensors to automate their production and management support structures. This is further supported by (Salijeni, Samsonova-Taddei, and Turley, 2019) who argued that the phrase "data scientist" has become more popular in auditing, implying that auditors regard themselves as seasoned experts, at least when it comes to data processing and analysis (Salijeni, Samsonova-Taddei, and Turley, 2019).

Figure 2: AICPA's Five-Step Audit Data Analytics Process



Because big data is so diverse and fast-paced, traditional data processing technologies cannot gather or analyze it (Markus & Topi, 2015). Big data, on the other hand, can be mined for insights that lead to improved strategic actions and decisions. According to Bierwirth (2019), incorporating data analytics into the internal audit function is not easy, but the work and money committed will assist organizations and businesses, stay on the cutting edge of technology and remain relevant in a fast-paced corporate environment. Although the rise of big data is undoubtedly not the first example of years of systematic experimental work in auditing, it is particularly intriguing since it brings into question of if Big Data audit settings, which place major technical requirements on auditors and increase their remoteness, are making a contribution to the audit function's systemic discrimination (Alles, 2015).

The use of analytics in auditing is still in its early stages, according to the findings of Protiviti's 2018 Internal Audit Capabilities and Needs Survey, and many audit processes are likely using analytics tools as point solutions rather than as part of a broader strategy to leverage analytics all across the audit process. Protiviti (2018) analyzed worldwide data from over 1,500 participants from the manufacturing, U.S. healthcare industries, and U.S. financial services and were asked to assess industry-specific skills. Respondents come from a variety of industries and work in government, private, government, and non-profit sectors. More than half of the respondents work for companies with annual revenues of more than \$1 billion. The top eight goals for internal audit programs, according to Protiviti's (2018) research, are displayed in Figure 3, and most of these areas are data-intensive, making them perfect candidates for analytics.

It is widely acknowledged that ADA does have the potential to revolutionize the auditing sector. When using ADAs for value generation, however, there are major challenges in terms of data availability, analytical tools, analytic programming, and administration for a variety of applications. The next section discusses some of the problems that can arise when employing ADAs.

5. AUDIT DATA ANALYTICS CHALLENGES

In audit engagements, data analytics has now been stressed as a useful tool. While there is great promise for incorporating ADA to improve audit quality, broad use of ADA on audits necessitates numerous considerations. Despite the potential of ADA in increasing audit quality, widespread use of ADA in audits has significant hurdles. Researchers have identified substantial challenges in terms of data, methods, analytic modeling, and management for a variety of



Figure 3: Data-Driven Decision-Making & Audit Data Analytics Priorities

applications in order to produce deep knowledge and meaningful insights from ADA for creating value. For example, Earley (2015) discussed ADA challenges under three broad categories: (1) training and expertise of auditors; (2) data availability, relevance, and integrity; and (3) expectations of the regulators and financial statement users.

According to McGregor and Carpenter (2020), the new technology will necessitate substantial financial and non-financial expenditure. The 'Big 4' audit firms would be more positioned than auditing firms to handle their clients' expectations using emerging technologies because of their vast international networks. Additionally, if the programs are not properly maintained, they will fail. Hackers may be able to manipulate the system and steal or destroy confidential client information (Zhang, 2019; Cangemi & Brennan, 2019). Auditors may offer additional services linked to securing the blockchain system and validating digital assets in terms of smart contract assurance (Deloitte, 2019).

To standardize various measurements, additional financial as well as non-measures, and also new technology and programming techniques, are necessary (Vasarhelyi *et al.*, 2015). Students and new professionals need to be properly taught, and teachers must adapt the classroom curriculum to contemporary global trends and issues (Janvrin & Watson, 2017). Additionally, if the programs are not properly maintained, they will fail. Hackers may be able to manipulate the system and steal or destroy confidential client information (Zhang, 2019;

Cangemi & Brennan, 2019). Auditors may offer additional services linked to securing the blockchain system and validating digital assets in terms of smart contract assurance (Deloitte, 2019).

Likewise, the new big data-based environment comprises information sources that are foreign to auditors, demanding a reassessment of audit evidence criteria (Appelbaum, 2016). Audit standards should be modified, according to Kend and Nguyen (2020), to make it much easier for auditors to embrace emerging technology and solve the dangers it poses. Data analysis, according to Samsonova, Salijeni, and Turley (2019) might be considered a disruptive audit technology.

6. CONCLUDING REMARKS

This article discusses the improvements audit analytics would bring to a domain, as well as its benefits, limitations, and drawbacks. It also looks into the use of big data and analytics in making data-driven decisions. According to academics, the development of Big Data is both a source of opportunity and a source of problem for social sciences such as accounting and auditing, both of which are data-intensive areas (Dagiliene & Kloviene, 2019).

Big data has the potential to generate enormous value by making additional kinds of data available and usable at a faster rate, enabling the creation of new products and services, continuous improvement, and more informed decision-making (Manyika *et al.*, 2011). To stay competitive, modern firms and organizations are eager to adopt cloud and Internet sources of data, such as social media (Balios *et al.*, 2020 a). Extensions of audits into Big Data utilization, as well as the conceptualization of duties in an age of artificial intelligence and automation, all have bright possibilities in the coming decade (Brynjolfsson & McAfee, 2014). Big Data has the potential of being incredibly valuable in auditing, and it seems that in the future, many auditing activities will be routinely uploaded into computer systems, making the job of auditors much easier. Paper documents will be reduced in number, and data will be handled, monitored, and audited online, potentially cutting accounting and tax periods in half (Horak & Boksova, 2017). Internal audit departments, in particular, may make Big Data integration easier in the long run. As a result, big data could provide higher intellect and knowledge, allowing previously unobtainable insights to be generated while keeping the illusion of truth, neutrality, and accuracy (Boyd & Crawford, 2012). However, due to the complexity of analyzing massive data, a paradigm shift from traditional information analysis is required (Grover & Kar, 2017).

Data-driven judgments continue to fail, notwithstanding the many expectations of technology, automation, and AI, and this needs to be researched and remedied (Elgendy, Elragal, & Päivärinta, 2021). Big Data is a developing business phenomenon and auditing systems must evolve to meet the problems it poses. Therefore, the right technology, processing power, and algorithmic precision are required to collect, analyze, link, and compare such datasets. Big data alone will not give firms a sustainable competitive advantage; they will also need the ability to gather data from multiple sources, evaluate big quantities of information, and so on.

Meanwhile, there are significant obstacles in relation to the data, processes, analytical modeling, and management for various applications in order to develop a deep knowledge and usable insight from ADA for creating value. Auditors will be required to follow management's lead in adopting Big Data, according to Alles (2015). In today's company climate, a more technologically advanced audit data analytics methodology and a more technologically educated auditor may be necessary for success. In addition, new standards may help overcome the auditing profession's resistance to working with big data (Gepp *et al.*, 2018). A long-term data analytics approach, according to Gepp *et al.* (2018), should stress the possibilities of auditing in relation to real-time information, collaborative networking, and peer-to-peer platforms.

To conclude, Data Analytics entails employing technology and statistical analysis to watch corporate operations, analyze performance, and present financial data more meaningfully. Data analytics entails using technologies and statistical methods to watch corporate operations, analyze performance, and present financial data in more meaningful ways. Although DA has long had a role in accounting, the amount and variety of data acquired and included in the analytical analysis have increased dramatically in recent years. According to the findings of Protiviti's 2018 Audit Skills global survey, the use of data analysis in auditing is still in its early stages, and several assessment procedures have been probably utilizing advanced analytics as application services rather than as part of a larger action plan to enable analytics all across the assessment process (PRNewswire, 2018). Big Data's availability will result in significant changes in the auditing profession, education, and research.

Acknowledgement

The authors appreciate the reviewers' comments and editorial assistance on this paper. This helped in improving the quality of the manuscript.

Conflict of Interest: There is no conflict of interest involved in the publication of this paper

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