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The Impact of Using Business Intelligence on Potential Fraud Detection: An Experimental Study

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Abstract

Fraud has become more common over the last few decades, as major corporations like WorldCom, Enron, and Satyam have gained notoriety for their dishonest financial reporting techniques. Internal and external auditors identify only a small portion of fraud incidents as such, there is a growing emphasis on automated techniques for identifying fraudulent financial statements. Accordingly, the main objective of this research is to investigate the impact of data analytics tools viz data visualization using Microsoft Power BI by auditors in fraud detection. An experiment of 49 participants was conducted to examine the research hypotheses and fulfill the research objective. The experiment results revealed that data visualization led to a timely fraud detection than traditional methods. Also, the use of data visualization led to more accurate fraud detection with regards to locating the potential fraud and the magnitude of the potential fraud as well. Hence, his research leads to practical follow-up steps that would serve as a guideline for forensic accounting auditors and to focus on areas of potential fraud. In order to develop a better fraud detection visualization tool, future researchers, auditors, law enforcement organizations, and regulators can benefit greatly from the knowledge this research provides. Also, auditing professionals that embrace big data, data analytics, and artificial intelligence (AI) to stay ahead of the competition can take advantage of many opportunities in this quickly changing, disruptive, but ultimately beneficial environment.

Key words: data visualization, audit, fraud detection, and business intelligence

1. Introduction

Every aspect of corporate life is changing as a result of technology, including how products are used and how company procedures are carried out (Christensen, 2013). It was highlighted that technology and the increase of data have provided an enormous depth of financial information reports and opened up a world of new opportunities for corporate growth.

The reduced line items in the financial accounts no longer fairly depict corporate activity as data is the most precious asset for organizations. Moreover, businesses are very reluctant to provide any specific information out of concern that doing so might harm their ability to compete by giving competitors access to trade secrets, which would reduce their competitive advantage. Past researchers have provided compelling evidence that the usefulness of financial statements has waned over time. For instance, despite having a long history of operational shortcomings, Tesla Inc. and Amazon Inc. outpaced the market (Lev & Gu, 2016).

The volume and complexity of accounting transactions have significantly increased as a result of technological improvements, posing both considerable opportunities and challenges for auditors. The advent of various information systems to be able to analyze and interpret such "Big Data" was facilitated by the continual exponential expansion in data volume (Brown-Liburd et al., 2015a). Big data has the power to fundamentally alter how auditors make decisions, including those pertaining to risk assessment, audit evidence, and audit methods (Gray & Debreceny, 2014). Thus, auditing is being radically altered by the developing data analytics revolution, which is being driven by powerful computer resources, cloud-based storage, enhanced modelling, and artificial intelligence (Appelbaum et al., 2017). With the use of data analytics tools, auditors may quickly and efficiently evaluate and interpret virtually any amount of data without jeopardizing the efficiency of their information processing (Brown-Liburd et al., 2015a). There are numerous data analytics tools that were introduced to the market throughout last decade, of which BI dashboards. BI Dashboards are anticipated to enhance cognition and take advantage of human perceptual talents to better decision making. As a result, interest in dashboards has grown recently, which is also demonstrated by the market's abundance of dashboard solution suppliers. Despite dashboards' widespread use, nothing is known about how successful they are especially for auditors.

Based on numerous calls of (Cunningham & Stein, 2018; Morar et al., 2019;Salijeni et al., 2021) to examine the utilization of data analytics tools with respect to BI in the auditing profession in the context of fraud detection, **the objective of this research** is to test the impact of data visualization tools, namely Power BI on fraud detection versus traditional financial statement fraud detection. Thus, **to fulfil this objective**, the author relied on an experiment of 49 participants divided into three samples. Based on the main analysis conducted, there was significant difference between sample that used traditional methods versus Power BI. Also, there was significant difference between the sample that used both traditional and Power BI, and traditional only. While there was no significant difference between the sample that used only Power BI and that used both traditional and Power BI. Results show that auditors will be able to detect potential fraud using Power BI in shorter time and more accurately than auditors using traditional methods.

The importance of this research stems from the emergence of one of the most crucial challenges facing auditors in big data era and its significance in fraud detection. The study adds to the stream of prior researchers in the area of data analytics in the auditing field as it investigates how data visualization adds value through time saving and accuracy in fraud detection. **This paper contributes to prior literature** in two facets. First, it documents experimental evidence on the impact of data visualization on fraud detection for auditors. Second, with the use of business intelligence fraud detection methods, this study has made a significant contribution to bridging the theoretical and practice gap in auditing profession. **This research will proceed** as follows: the literature on business intelligence and big data, business intelligence and auditing profession, and fraud detection and data visualization are discussed in section 3, and then the research hypotheses are developed. While sample selection and experimental design are presented in section 4. Later, in section 5, descriptive statistics, main analysis, and additional analysis are discussed. Lastly, section 6 concludes and provides implications for future research.

2. Literature Review

The next section is divided into four subsections; the first discusses the business intelligence and big data, the second highlights the relation between business intelligence, big data and the auditing profession. While the third part presents prior literature concerning fraud detection and finally the fourth part presents the relation between fraud detection and data visualization.

2.1 Business Intelligence and Big Data

Although the phrase "big data" is relatively not new to the commercial sector, it is already widely employed in almost every aspect of human endeavor. Big data's widespread use is largely due to recent developments in information technology, particularly the internet, which have made an exponentially increasing amount of information accessible (Vasarhelyi et al., 2015a). Additionally, businesses struggle with ineffective procedures that cause chaos across the board and squander vital resources like time, money, energy, and bad decision-making. Decision-makers frequently receive financial statements days or even weeks after a period ends because data must be manually aggregated from several sources (Drum & Pulvermacher, 2016)

Big data refers to information assets with large volume, high velocity, and high diversity that require creative and cost-effective forms of information processing to improve decision-making, insight, and process optimization. Therefore, these "three Vs"—volume, velocity, and variety—define big data (ACCA & IMA, 2015)

These massive data sets appear to present the possibility of gaining access to previously believed to be unattainable types of knowledge and insight. Few, if any, would contend that the importance of such data to business should be disregarded, as it seems to have unquestionable value. Clearly, the true issue is how to exploit it to its fullest potential (Kimble & Milolidakis, 2015). But on the other hand, in order to get the maximum value from the data, modern organizations frequently struggle to organize the deluge of data that is available to them in an efficient and effective manner (Drum & Pulvermacher, 2016).

Dow et al., (2021) added that big data by itself has limited value; the benefit of big data is only seen when an accountant uses technology and critical thinking to successfully use data. In other words, Big Data and Business Intelligence namely Data Analytics together can provide answers to a wide range of crucial queries. As a result, the true value of big data analytics lies not in the quantity or complexity of the data itself, but in the quality with which the data is analyzed to produce actionable intelligence, which necessitates the use of the appropriate data in conjunction with the appropriate analytical tool.

More precisely, big data is generally acknowledged as the upcoming area of innovation, competitiveness, and efficiency (Manyika et al., 2011). According to a survey done by the McKinsey Global Institute in 2012, big data and data analytics are viewed as the highest priorities in current business functions by 51% of global business leaders. Additionally, the Chartered Global Management Accountant found (CGMA) that big data will completely transform the way firms run over the next ten years after surveying over 2000 Chief Financial Officers(CFOs)and finance experts worldwide CGMA 2013).

In accounting and auditing, data analytics is a relatively new skill set that is rapidly expanding across the board. Over time, the benefits of data analytics in accounting, auditing and finance have become increasingly valuable. In fact, data analytics has completely changed work processes, especially those that give decision-makers and information users assurance, predictions, and conclusions. As a result, data analytics is seen by accounting academics, researchers, and practitioners all around the world as a useful tool for learning new things about a company's finances, finding areas for process improvement, and lowering risk (Austin et al., 2021).

Due to the massive volume and high velocity of data, automatic real-time data analysis is now a major component of continuous auditing applications. But there are gaps between the need for big data analytics and current audit analytics because of large volume and high velocity. Due to the existing auditing method's limited ability to handle massive data, the enormous variety and high veracity also create new issues (Bose et al., 2023).

2.2 Business Intelligence, Big Data and the Auditing Profession

In recent years, the term "Big Data" has gained popularity in the accounting industry, joining other popular subjects like blockchain, artificial intelligence (AI), and machine learning (Bose et al., 2023). Similarly, the number of internal and external data sources within organizations have increase drastically, massive amounts of data are available for decision-making. To enhance decision-making, stakeholders frequently demand that nonfinancial data be added to financial reports. This calls for sufficient proficiency with and familiarity with data analytics Spreadsheets are a common tool used by most accountants, although their functionality is restricted (Frans et al., 2019).

Businesses have already invested more than $150 billion on data analytics, and over the next several years, this amount is expected to increase by about 45% (International Data Corporation, 2019). These days, accounting specialists all around the world analyze and understand the vast amount of accounting data, the majority of which originates from non-traditional accounting systems, to provide important support to their senior executives (Davenport& Harris, 2017). Austin et al., (2021) added that added that audit companies have committed to spending previously unheard-of sums of money, time, and resources on data analytics and technology, which may significantly alter the current financial statement audit procedure.

It is challenging to forecast how automation will affect any given occupation. Davenport & Kirby (2016) predicted that there will be a rise in automation of certain operations carried out by tax and audit accountants in 2016. But just few years ago, the compliance work that auditors conducted was expanding rapidly and was seen as a promising vocation (Huerta & Jensen, 2017a).

KPMG (2015) observed that as auditing evolved, auditors needed to employ increasingly advanced tools for data analysis. Similarly, audit firms have proposed that the use of visualization aid in the study and presentation of audit issues (O'Donnell & KPMG, 2017). One argument put out was that auditing data gathering will become more automated and include the acquisition of data at a finer level. Additionally, audit sampling will be performed on the entire population rather than just a sample, freeing up auditor time for activities requiring higher cognitive skills. Additionally, assurance will shift from highlighting and identifying specific misstatements to highlighting and identifying potential frauds before misstatements(Krahel& itera, 2015).

Furthermore, big Data has the benefit of being easier for computers to read. This same benefit gives rise to one of the main obstacles auditors encounter when working with large data: its unstructured nature. For conventional analytical tools like Microsoft Excel or Microsoft Access to function properly, organized data is necessary (Brown-Liburd et al., 2015b). Notwithstanding, big data analytics can help accountants expand their monitoring strategies to encompass both structured and unstructured data, opening up new avenues for future advancements.

Data analytics, according to academics and practitioners, may more effectively disclose insights, patterns, and anomalies than traditional methods, changing the way corporate choices are made (KPMG, 2015). Furthermore, the utilization of additional data analytics features, especially interactive dashboards made to display analytics results in ways that create new affordances. The purpose of these dashboards is to enable auditors to generate evidence that can be utilized for new or supplementary audit procedures, like substantive, analytical, and risk assessment procedures. The results revealed that interactive reports that support audit decisions may be produced using visualization dashboards, and those decisions can then be communicated to parties outside of the audit in a way that seems credible and authoritative (Salijeni et al., 2021).

The diffusion of data analytics—that is, the entwined development, usage, and spread of data analytics throughout financial reporting, auditing, and regulatory processes—has been slower than one may have predicted, despite these seeming benefits (Austin et al., 2021). Similarly, Vasarhelyi et al., (2015b), stipulated that the expansion of accounting data sets can have several practical uses, such as: (1) processing and analyzing detailed transaction data instead of summary; (2) integrating a variety of external and internal data with financial data for analysis; (3) enabling "soft integration" of environmental Big Data (like social media and news articles) with accounting measurement and audit assurance procedures; and (4) transforming accounting, business, and audit processes based on the aforementioned.

Hence, auditors must stay up with technological advancement and be ready to take advantage of it in order to give better insights based on new capabilities and the increased volume of data that is available (KPMG, 2015). With the technological abilities, the relevance and timeliness of accounting numbers and analysis will increase. Similarly, business measurement and assurance must change and automate more as a result of these disruptive information technologies if they are to keep their value to the organization and its numerous stakeholders (Vasarhelyi, 2012).

On the other hand, it has been discovered that cutting edge technologies, such data mining and predictive modeling, are useful for assessing fraud risks through the analysis and evaluation of large amounts of data. Negative correlations, for instance, between nonfinancial and financial firm performance metrics may be a sign of financial information manipulation. However, even in the Big Data world, there are still obstacles that can't be solved by cutting-edge technologies on their own. Interpretation and judgment are still involved in decisions based on data from big data. For example, while technology can detect patterns, an auditor is still required to assess and examine these patterns. While these technologies can help organize data and aid in decision-making, analysis would not be more effective or efficient or audit quality enhanced if auditors did not organize and use the information, they have discovered (Brown-Liburd et al., 2015b).s

2.2.1 Big Data Tools in Auditing

A business can evaluate its financial performance and position from multiple perspectives by utilizing a variety of methods. The following auditing data analytics technologies are available for use by organizations to handle their data.

2.2.1.1 Microsoft Excel

Businesses all over the world use Microsoft Excel, a spreadsheet program that runs on Windows, macOS, Android, and iOS platforms. Its features are numerous and include data processing, number summarization, pivot tables, graphing tools, and more. Regression modeling is one statistical analysis that Microsoft Excel can do. One of the most important and powerful data analytics tools available is Microsoft Excel, which raises user expectations for efficacy and efficiency. Also, the days of Excel being a nice-to-have talent are long gone. Employers anticipate accounting students learn proficiency in spreadsheet software before they graduate (Schönfeldt & Birt, 2020).

2.2.1.2 Machine Learning Tools

A software model is trained on data through the data analysis approach known as machine learning. This area of artificial intelligence is predicated on the idea that machines are capable of learning from training data, spotting patterns, and rendering decisions with little to no assistance from humans. The most cutting-edge and complex tools, like "R" and "Python," are used by several businesses worldwide in their data analytics accounting processes. Most businesses use these programming languages to carry out highly customized and sophisticated statistical analyses (Praful Bharadiya, 2023).

Transaction processing is increasingly using machine learning. In addition to being knowledgeable about these technologies, accountants must also comprehend the procedures involved in creating guidelines and risk assessments for the controls. This calls for the ability to integrate accounting knowledge with an awareness of automated systems and programming as well as a comprehension of the intricate process rules that enable machine learning to function—more than before (Frans et al., 2019)

2.2.1.2 Business Intelligence Tools

Business intelligence technologies that enable accounting professionals to get predicted and sustainable insights from a given dataset may be of use to them. A corporation can clean up data, model data, and produce clear visuals by utilizing a range of business intelligence technologies (Poddar, 2021). This visualization offers thorough comprehension and aids in identifying areas in need of additional work. These technologies produce some common qualities that other group members can readily access and comprehend. Numerous business intelligence solutions are available, including Zoho Analytics, SAS Business Intelligence, Oracle Business Intelligence, Tableau, Power BI, Data pine, and Good Data (Bose et al., 2023)

2.2.1.3 Visualization Tools

Both managers and auditors mention utilizing a range of tools for their analytics, from artificial intelligence to Excel-based analysis. Many talk explicitly about creating graphical representations of data, or visualizations, utilizing Tableau or Power BI to find patterns and abnormalities in the data of their clients. The software tools that auditors use most often to create visuals that show and analyze links between their customers' financial data are Tableau and Power BI (Austin et al., 2021; O'Leary, 2022; Raschke & Charron, 2021)

The graphical display of data is known as data visualization. Data visualization software makes it possible for users to examine and comprehend data in ways that were previously only possible with the use of intricate queries and laborious manipulation. Data visualization helps users understand the data. It is unlikely that significant information can be gleaned or problem areas may be identified by simply going through a large data set line by line. Large data sets can be swiftly and efficiently displayed in a variety of ways by using data visualization software, which can produce numerous graphs, charts, and other visualizations from the data. It is simple to alter the visualizations to incorporate fresh data or perform other analyses on the same. These graphs make it simpler to see the big picture and spot patterns and trends in the data that were hidden in the original format (Hoelscher & Mortimer, 2018)

In order to augment functionality, business intelligence (BI) combines data mining, visualization, and analysis from company operations and activities. BI offers a thorough understanding of the data, which is utilized to inspire change. The visual depiction of data is known as data visualization. It is a fundamental tool for understanding big Data since it articulates the narrative that make the data simpler to comprehend. Data visualization enables the analyst to easily spot outliers that require further study and spot trends or patterns in the data (Kitching et al., 2021). Visualization enables managers to quickly understand the findings of complicated investigations, those tools have grown in popularity as a result of big data. This has helped managers make more informed decisions across a variety of domains. Big data could be transformed into knowledge that is useful for making decisions thanks to visualization (Huerta & Jensen, 2017b).

2.3 Fraud Detection

Corporate fraud refers to managerial behavior that, rather than operating in the best interests of the firm's stakeholders, favors some stakeholders at the detriment of others out of self-interest. The Association of Certified Fraud Examiners states that the three main types of corporate fraud are asset misappropriation, corruption, and misleading financial statements. Financial statement fraud is the least common (10%) and most costly (with a median loss of $954,000) among these, whereas asset misappropriation is the most common (86%) and least expensive (with a median loss of $100,000). Typically, fraud and misappropriation cost organizations 5% of their yearly income (ACFE, 2020). A financial statement fraud can destroy an economy if it is not discovered in time (Shahana et al., 2023).

Auditors need to gather, analyze, and synthesize a lot of data from different sources in order to make choices. This is not an easy task. It is also widely acknowledged that inefficient auditing procedures have less of an impact on audit failures than difficulties in spotting patterns suggestive of management fraud or going-concern concerns (Brown-Liburd et al., 2015b). In a similar vein, automated visual walkthroughs should enable the management and auditors to identify and address irregularities(Wong & Venkatraman, 2015). Even with the existing criteria in place, fraud events may be hard to find. The auditors are tasked with identifying irregularities in the financial statements. However, only a small percentage of fraud cases are detected by internal and external auditors (15 percent and 4 percent, respectively) (ACFE, 2020). Consequently, there is an increasing focus on automated methods to detect false financial statements. These technologies are especially necessary for government regulatory authorities to focus their investigations, accounting and auditing firms to perform audits quickly and properly, and shareholders to make well-informed decisions (Agrawal & Cooper, 2015).

2.4 Data Visualization and Fraud Detection

Financial institutions have had to deal with a rise in financial crimes recently. In this environment, financial services companies began to increase their level of alertness and employ new tools and strategies to spot and anticipate potential financial fraud and criminal activity. This is a difficult undertaking since organizations must improve their data and analytics capabilities in order to use emerging technologies, including artificial intelligence (AI), to anticipate and identify financial crimes (Rouhollahi et al., 2021).

Big data analytics was divided by (Russom, 2011) into four main categories based on organizational commitment and possible expansion (of use); these factors include the tool's expected rise or fall in popularity as well as the possibility that the business will continue to use it. The first category, which encompasses statistical analytics, machine learning, artificial intelligence, predictive models, and visualization approaches, is anticipated to see significant development in popularity. **Real-time analytics** is one example of this group; it analyses data and updates dashboards used by **auditors** or management to spot issues instantly. This group also includes text-mining tools, which are becoming more and more well-liked because they can be used to solve a variety of issues, including **fraud and risk evaluations**. Data warehouses and specialized database management systems make up the second category. These analytics are expected to see a higher adoption rate because there are more platforms available. Businesses can choose from a range of solutions, many of which are loaded with in-built analytics, also known as in-database analytics, which can make it easier for auditors to examine the data. Even though the third group has the advantage of using distributed computing, it is still relatively new and not generally known to auditors. Given the dispersed nature of collected data due to globalization, this skill is particularly crucial. These systems, such the Hadoop Distributed File System, allow auditors to work with a variety of data types and sources, including text and financial data. The tools that are now in use by most businesses and are predicted to eventually become obsolete owing to their restricted scalability are included in the last group. Examples of these tools are traditional database management systems, which were created for traditionally structured data.

Singh & Best (2016) implemented multi-view dashboard, which makes it easier for auditors to examine big databases of accounts payable transactions. An interactive dashboard that offers a high-level summary of all the activities carried out, graph visualizations that illustrate the links between users, vendors, and transactions, and normal structured query language (SQL) queries are the tools used in this interactive method. With this method, a vast amount of transaction data is rapidly filtered and aggregated, allowing an auditor to quickly spot patterns or relationships in the data that would otherwise be challenging to find in textual data. The results revealed positive feedback from auditors. They discovered that the visuals were helpful in combining vast amounts of data and were simple to grasp. Additionally, it was believed that visualizations made it easier to spot patterns or relationships in the data than it would be in written form. The panel assessed the visualizations as useful and inventive tools for a fraud investigator's toolset overall.

While process mining uses the underlying dataset to reconstruct and depict the business process as it is, the red flag approach provides clues for anomalous behavior. When these two methods are combined, it becomes possible to identify potential fraudulent process instances and visualize them together with the associated red flags (Baader & Krcmar, 2018) effectively identified 15 out of 31 fraud cases in their dataset by applying a novel approach to the purchase-to-pay business process in an exemplary manner. The false positive rate was 0.37 percent, which is far less than what has been documented in other studies of a similar nature. In the same line stream, Collaris et al., (2018) created two innovative dashboards that combine several cutting-edge extraction techniques. These greatly accelerate the process of highlighting out possible fraud cases by enabling the domain expert to evaluate and comprehend predictions. The study found that although the outcomes of various visualization procedures can range greatly, they can all be regarded as valid and helpful.

Cunningham & Stein (2018) added that the accounting industry has changed recently, and auditors now need to graduate with technical and analytical abilities that can be applied to big datasets. The capacity to spot irregularities and risk indicators in the client's data is a crucial ability in an audit scenario. Utilizing links between financial data namely revenues and nonfinancial data, an instructional case was developed to give students practice using visualization to find anomalous transactions for additional substantive testing. In addition, the students who was proxied auditors, were required to write a statement for the workpaper files outlining their conclusions and suggesting which sales transactions should be chosen for substantive testing by the audit team. In addition to giving students practice with Tableau visualization software, this research reported an enhance analytical and problem-solving abilities for the participants by promoting individual effort and the division of difficult problems into manageable sections.

Morar et al.,(2019) designed a dashboard that analyze four forms of credit card fraud at varying computer confidence levels. A total of 27 participants in the **experiment** were given with different types of information on several dashboards. Effective pop-up use was defined based on the data they provided and the kind of fraud under investigation. The findings indicate that even in situations where information is not needed, participants would go deeper for it. When the window is not needed, participants, at least with the list pop-up, swiftly dismiss it. The study results revealed that giving participants clear dashboards, training them to criterion, and giving them an aide memoire to define the task all contribute to ensuring consistency in decision making, which in turn relates to strategy conformity.

The findings of Salijeni et al.,(2021)have demonstrated the technique's value in identifying fraud signs so that management can conduct follow-up, investigative measures that will facilitate ongoing progress. As a result, this work has made a significant contribution to closing the knowledge gap between theory and practice by proposing novel approaches, such trend analysis employing knowledge discovery techniques, and utilizing established fraud detection techniques, such as vertical and horizontal analysis. This study has significantly contributed to closing the theoretical and practical gaps in fraud detection through the use of common fraud detection techniques such as vertical and horizontal analysis. It has also suggested a novel approach like trend analysis employing knowledge discovery techniques. Additionally, the dashboard for visualization demonstrates how it is used to compile data and look for odd trends. In addition to providing data aggregation, the visualization dashboard allows users to drill down into specific transactions, like those in a sales journal, to readily identify key data points like the person making the entry, the time it was made, and the person who authorized it.

From the above discussion and analysis of prior literature, it can be emphasized that information overload brought on by big data affects auditor performance and judgment. In order to use BI effectively, auditors will need to increase their tolerance for ambiguity and employ data analytics to exaggerate common data problems they run into when reviewing large samples of transactional data or the entire population. Additionally, the need for data analytics tools, particularly data visualization, is driven by automated audit systems and a variety of highly probabilistic types of evidence. **In order to fulfill the *research objective,*** *the following research hypotheses can be formulated:*

H1: Business Intelligence tools will detect potential fraud in less time than traditional tools.

H2: Business Intelligence tools will detect potential fraud amount compared to traditional tools.

H3: Business *Intelligence tools will detect potential fraud location compared to traditional tools*.

The above hypotheses are summarized in the following research model.

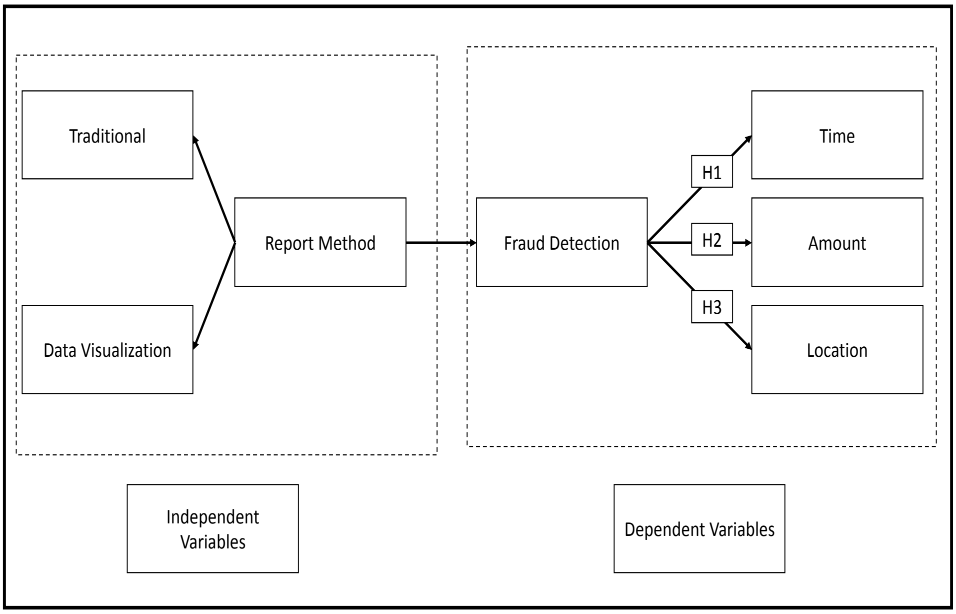

Figure 1: Research Model (Developed by the author)

3. Research Design and Methodology

The research methods, sample selection, measurement of the dependent and independent variables utilized in this study, and development of the research model will all be covered by the author in this section.

3.1 Research Methodology

This research relied on an experiment to test the research hypotheses and fulfill the research objective. In which, an experiment is a way to manipulate variables in order to find relationships between them and to confirm or deny theories. The purpose and scope of experiments differ greatly, but all of them rely on logical analysis of the data and reproducible processes. Accordingly, an experiment was carried out in this research to determine decision-making processes when utilizing dashboards versus traditional accounting reports followed by a post-case survey (Cunningham & Stein, 2018). Thus, financial data from a hypothetical firm was obtained and used in the experiment where two reports were generated from the same financial data which had a potential fraud in one of its accounts; the first report was generated in a traditional format, financial statements including statement of financial position, income statement and cash flow statement for five years; 2018 to 2022, the second report was generated from the same data but using business intelligence Power BI resulting in a dynamic dashboard that presents all financial data (Morar et al., 2019).

3.2 Research Sample

The experiment focused on one general category of users which are the auditors, people whose profession is directly related to the study. In this research, students in fourth year were used as a proxy for auditors (Schönfeldt & Birt, 2020). Those students accomplished two criteria to be selected in the research sample; the first criteria, student must have completed the computerized auditing techniques course which focuses on a comprehensive overview of the auditing profession with special focus on computerized tools that auditors can use and software tools course which mainly focus on data analytics tools and data visualization that can be used by accounting and auditing professionals. The second criteria, student must have the necessary power BI skills required for the experiment, thus, students were tested forehand for their skills to be accepted into the experiment. This gives us a homogeneous user base from which to investigate how dashboard designs affect decision-making capabilities.

Followed by the sample selection, students were divided randomly into three samples to serve the research objective.

3.2.1 Sample One:

After being directed to a designated computer lab at Egypt Japan University For Science an Dtechnology (E-JUST), students were given guidelines to follow beforehand, including timing themselves. After that, each of them took a seat in front of a different computer and had access to the dashboard for review**. Data from a hypothetical company's five-year income statement, cash flow statement, and statement of financial position were all included in the dashboard** (from 2015 to 2019).

3.2.2 Sample Two:

A different group of students were guided to a predetermined computer lab in E-JUST where they were given certain instructions to follow before they started such as to time themselves. Then, they were seated each on a separate computer with the dashboard and five-year hard copy of the financial reports available for their consideration. **Data from a hypothetical company's five-year income statement, cash flow statement, and statement of financial position were all included in the dashboard and the hard copy reports** (from 2015 to 2019).

3.2.3 Sample Three:

Another group of students were led to a designated E-JUST classroom where they were given guidelines to follow beforehand, including timing themselves. They were then given separate seats and given access to a paper copy of the financial reports for the previous five years for review**. Data on a hypothetical company's income statement, cash flow statement, and statement of financial position were included in the five-year hard copy of the financial statements** (from 2015 to 2019). Participants were instructed to use traditional methods for potential fraud detection on the five years financial reports using vertical and horizontal and ratio analysis for red flag to be identified (Bratsas et al., 2021).

3.3 Research Variables

The following subsection presents the research variables as follows:

3.3.1 Independent Variables:

There are two independent variables in this study. The conventional financial reports for a fictional corporation from 2018 to 2022 are the first independent variable, and the dashboards are the second.

In order to ascertain the relationship between various factors for investigation and information, traditional financial statement analysis involves analyzing financial or accounting data that was taken from financial statements using traditional analysis tools of basic techniques like accounting ratios, intra-firm comparison, percentage of inter-firm comparison (Baader & Krcmar, 2018; Bratsas et al., 2021).

The data dashboard (generated by business intelligence Power BI) is an information management tool that helps you monitor a certain process or your organization by tracking, analyzing, and displaying metrics, data points, and key performance indicators (KPI) (Collaris et al., 2018).

3.2.2 Dependent Variables:

The study includes three dependent variables:

(1) the ability to locate the potential fraud, which was measured using a dummy variable: 0 for yes and 1 for no (Hoelscher & Mortimer, 2018; Morar et al., 2019)

(2) the ability to identify the year and magnitude of the potential fraud, which was also measured using a dummy variable: 0 for correct year and amount, 1 for wrong year and/or amount (Hoelscher & Mortimer, 2018; Morar et al., 2019)

(3) the time it took for each student to locate the potential fraud (Cunningham & Stein, 2018;Morar et al., 2019)

3.2.3 Control Variables:

In this research, there are two control variables adopted in prior literature (Dzuranin et al., 2018):

(1) Gender: measured as a dummy variable, 1 for male and 2 for female.
(2) CGPA: measured as a categorical variable with a scale from 1 to 6, where 1 for CGPA more than 3.7 and 6 for CGPA more than 2.00.

4. Empirical Results

4.1 Descriptive Statistics

The findings of testing the research hypotheses were reported in this section after the results of the descriptive analysis. is therefore broken up into three sections; the first section covered the descriptive statistics for the three samples and study variables (mean, median, frequencies, standard deviation, skewness and kurtosis). The fundamental analysis was covered in the second section (the results of the Kruskal Wallis and Mann- Whitney test). The further analysis was covered in the third and final section (the results of the control variables and their interaction with the research variables).

4.1.1 Results of Sample Descriptive Statistics

Forty-nine undergraduate students from year 4 were contacted through messages and emails, they were asked to participate in the experiment and a brief was sent to them. Upon students' approval to participate in the experiment, they were given the instructions for conducting the experiment on E-JUST premises.

Table 4- 1: Samples Demographic Characteristics

		Sample 1		Sample 2		Sample 3		Total	
		%	N	%	N	%	N	%	N
Gender	**Male**	45.7	7	27.3	3	12	2.2	22	4.9
	Female	53.3	8	72.7	8	11	7.8	27	5.1
CGPA	**>3.7 (1)**	13.3	2	1	9.1	1	4.3	4	8.2
	>3.3 (2)	20.0	3	2	18.2	3	13.0	8	16.3
	>3.0 (3)	26.7	4	2	18.2	7	30.4	13	26.5
	>2.7 (4)	33.3	5	1	9.1	2	8.7	8	16.3
	>2.3 (5)	6.7	1	3	27.3	4	7.4	8	16.3
	>2.0 (6)	13.3	2	2	18.2	6	6.1	8	16.3

4.1.1.1 Sample One:

The demographic characteristics for sample one depicted that 45.7% of the respondents were males while 53.3% were females signaling the dominance of the females in the sample. However, most of the sample had CGPA greater than 2.7 about 33.3%. while the least percentage of CGPA was greater than 2.3 about 6.7%.

4.1.1.2 Sample Two:

The demographic characteristics for sample two depicted that 27.3% of the respondents were males while 72.7% were females signaling the dominance of the females in the profession. However, most of the sample had CGPA greater than 2.3 about 27.3%. while the least percentage of CGPA was greater than 3.7 and 2.7 about 9.1%.

4.1.1.3 Sample Three:

In sample 3, The demographic characteristics for sample two depicted that 44.9% of the respondents were males while 55.1% were females signaling the dominance of the females in the profession. However, most of the sample had CGPA greater than 3.0 about 26.5%. while the least percentage of CGPA was greater than 3.7 about 8.2%.

The results confirm the homogeneity among participants with regards to CGPA and gender and thus overcoming sample bias and strengthening the robustness of the results.

4.1.2 Results of Variables Descriptive Statistics

The focus of the next section was relative frequencies of the categorical variables, percentiles, measures of central skewness and kurtosis tendencies; mean, median.

Table 4- 2: Results of Variables Descriptive Statistics

Sample	Variable	Mean	Median	St.D	Min	Max	Skewness	Kurtosis	N
Sample 1	Locate potential fraud	1.000	1.000	.000	1.0	2	.580	1.121	15
	Potential fraud magnitude	1.267	1.000	.703	1.0	3	2.405	4.349	
	Time in seconds	266.46	246.00	170.4	5.0	706.0	1.014	2.118	
Sample 2	Locate potential fraud	1.091	1.000	.3015	1.0	2.0	3.317	11.00	11
	Potential fraud magnitude	1.091	1.000	.3015	1.0	2.0	3.317	11.00	
	Time in seconds	255.72	216.00	209.710	65.0	793.0	1.815	4.107	
Sample 3	Locate potential fraud	1.609	2.000	.4990	1.0	2.0	-.477	-1.95	23
	Potential fraud magnitude	1.826	2.000	.777	1.0	3.0	.324	-1.22	
	Time in seconds	503.52	560.00	190.2873	105.0	820.0	-.427	-.410	

4.1.2.1 Sample One

In sample 1 it is shown in (Table 4-2), the mean for locating the potential fraud was (mean = 1.000) indicating that all were able to locate the potential fraud, while as for the standard deviation for this sample (S.D = .000) exhibited a low standard deviation indicating that responses were clustered towards the mean. As for skewness for this variable = .580 which is positive and close to 0 indicating a slight skewness of the responses to the right. For the kurtosis = 1.21 which is positive indicating leptokurtic heavy tailed responses. For the second dependent variable, potential fraud magnitude, mean of responses was

1.267 indicating that most students were able to identify the year and amount of the potential fraud correctly, while standard deviation = .7037 indicating that responses were distributed away from the mean. As for skewness = 2.405 which is positive and far from zero indicating right skewness of the responses while kurtosis was 4.349 which is positive indicating a leptokurtic shape form the responses. Finally, the third variable; time, mean was = 266 indicating that students were able to identify the potential fraud in almost 4.5 minutes with standard deviation of 170 indicating that responses are spread away from the mean. Furthermore, responses for time to identify the potential fraud with minimum time = 5 seconds while maximum was 706 seconds. In this sample skewness = 1.014 which is positive and far from zero indicating right skewness of responses, while kurtosis = 2.118 which is also positive indicating a leptokurtic shape for responses.

4.1.2.2 Sample Two

In sample 2 it is shown in (Table 4-2), the mean for locating the potential fraud was (mean = 1.091) indicating that nearly all were able to locate the potential fraud, while as for the standard deviation for this sample (S.D = .3015) exhibited a low standard deviation indicating that responses were clustered towards the mean. As for skewness for this variable = 3.317 which is positive and higher than 1 indicating a high skewness of the responses to the right. For the kurtosis = 11.000 which is positive indicating leptokurtic heavy tailed responses. For the second dependent variable, potential fraud magnitude, mean of responses was 1.091 indicating that almost students were able to identify the year and amount of the potential fraud correctly, while standard deviation = .3015 indicating that responses were distributed away from the mean. As for skewness = 3.217 which is positive and higher than 1 indicating right skewness of the responses while kurtosis was 11.000 which is positive indicating leptokurtic heavy tailed shape responses. Finally, the third variable; time, mean was = 255 indicating that students were able to identify the potential fraud in almost 4.25 minutes with standard deviation of 209 indicating that responses are spread away from the mean. Furthermore, responses for time to identify the potential fraud with minimum time = 65 seconds while maximum was 793 seconds. In this sample skewness = 1.815 which is positive and far from zero indicating right skewness of responses, while kurtosis = 4.107 which is also positive indicating a leptokurtic shape for responses.

4.1.2.3 Sample Three

In sample 3 it is shown in (Table 4-2), the mean for locating the potential fraud was (mean = 1.609) indicating that more than half were able to locate the potential fraud, while as for the standard deviation for this sample (S.D = .4990) exhibited a low standard deviation indicating that responses were clustered towards the mean. As for skewness for this variable = -.477 which is negative and close to 0 indicating a slight skewness of the responses to the left. For the kurtosis = -1.951 which is negative indicating a flat thin platykurtic responses. For the second dependent variable, potential fraud magnitude, mean of responses was 1.826 indicating that most students were not able to identify the year or amount of the potential fraud correctly, while standard deviation = .7777 indicating that responses were distributed away from the mean. As for skewness = 0.324 which is positive and far from zero indicating right skewness of the responses while kurtosis was -.410 which is negative indicating a flat thin platykurtic responses. Finally, the third variable; time, mean was = 503 indicating that students were able to identify the potential fraud in almost 8.3 minutes with standard deviation of 190 indicating that responses are spread away from the mean. Furthermore, responses for time to identify the potential fraud with minimum time = 105 seconds while maximum was 820 seconds. In this sample skewness = -.427 which is negative and far from zero indicating left skewness of responses, while kurtosis = -.410 which is also negative indicating a flat thin platykurtic responses.

4.2 Main Analysis Results

The next part presented the results of Kruskal Wallis test and Mann Whitney test. It was divided into two parts; part one discussed the Kruskal Wallis results the results of comparing all three independent samples as for the three dependent variables identifying the potential fraud, potential fraud magnitude and time required to locate potential fraud. Part two discussed the Mann- Whitney results of comparing each pair of independent samples thus it was divided into three subparts:

Comparison 1 between sample 1 and 2, comparison 2 between sample 2 and 3 and comparison 3 between sample 1 and 3.

4.3.1 Results of Kruskal Wallis Test

Referring to (Table 4-3), to compare between the three independent samples; sample one dashboard, sample two both dashboard and traditional and sample three traditional only thus, the use of Kruskal Wallis test in this experiment is essential to determine if there are statistically significant differences between the research variables; locating potential fraud, potential fraud magnitude, and the time in seconds. Regarding the research variable one and research hypothesis H1, there is significance in locating the potential fraud where p-value = .000) which is less than .05. Regarding the second research variable and the research hypothesis H2, there is significant difference between the three samples where (p-value = .003) which is less than .05. Regarding the third research variable and the research hypothesis H3, there is significant difference between the three samples where (p-value = .001) which is less than .05.

Table 4- 3: Kruskal Wallis Test

	Locate potential fraud	Potential fraud Magnitude	Time in seconds
Chi-Square	18.543	11.412	14.678
df	2	2	2
Asymp. Sig.	.000	.003	.001

Thus, it can be concluded that there is a significant difference between the three samples regarding the three research variables: there is significant difference in locating the potential fraud, identifying the potential fraud magnitude and in the time to identify the potential fraud. To shed more light on the difference between the three samples, further test and investigation were carried out as discussed in the following part.

4.3.2 Results of Mann Whitney Test

After comparing between the three independent samples using Kruskal Wallis test. Further investigation was needed where a comparison between each two samples was carried out independently using Mann

Whitney test. The following subsection is divided into three parts: part one discussed the results of Mann Whitney test to compare between sample one using the dashboard and sample two using both dashboard and traditional financial statements, part two displayed the results of Mann Whitney test to compare between sample two using both dashboard and traditional financial statements and sample three using only traditional financial statements and finally, part three displayed the results of Mann Whitney test to compare between sample one using and sample three using only traditional financial statements.

4.3.2.1 Comparison 1 between Sample 1 and 2

Referring to (Table 4-4), using Mann Whitney test to compare between the results of sample one and two, where sample one had the dashboard only and sample two had both the traditional and dashboard. It was concluded that there is an insignificant difference between the two samples with regards to locating the potential fraud since (p-value= .721) which is greater that .05. Also, there is an insignificant difference between the two samples with regards to identifying the potential fraud magnitude since (p-value= .838) which is greater than .05. And finally, there is an insignificant difference between the two samples with regards to the time to locating the potential fraud since (p-value= .610) which is greater than .05. Thus, it can be concluded that there is no significant difference between sample 1 using dashboard only and sample two using both dashboard and traditional financial statements.

Table 4- 4: Comparison 1

	Locate potential fraud	Potential fraud magnitude	Time in seconds
Mann-Whitney U	75.000	78.000	72.000
Wilcoxon W	195.000	144.000	138.000
Z	-1.168	-.421	-.545
Asymp. Sig.	.243	.674	.586
Exact Sig.	.721[b]	.838[b]	.610[b]

4.3.2.2 Comparison 1 between Sample 1 and 3

Referring to (Table 4-5), using Mann Whitney test to compare between the results of sample one and three, where sample one had the dashboard only and sample two had the traditional only. It was concluded that there is a significant difference between the two samples with regards to locating the potential fraud since (p-value= .001) which is less than .05. Also, there is a significant difference between the two samples with regards to identifying the potential fraud magnitude since (p-value= .014) which is less than .05. And finally, there is a significant difference between the two samples with regards to the time to locating the potential fraud since (p-value= .001) which is less than .05. Thus, it can be concluded that there is significant difference between sample 1 using dashboard only and sample three using traditional financial statements with regards the three research variables.

Table 4- 5: Comparison 2

	Locate potential fraud	Potential fraud Magnitude	Time in seconds
Mann-Whitney U	67.500	99.500	64.000
Wilcoxon W	187.500	219.500	184.000
Z	-3.752	-2.458	-3.241
Asymp. Sig	.000	.014	.001
Exact Sig.	.001[b]	.028[b]	.001[b]

4.3.2.3 Comparison 3 between Sample 2 and 3

Referring to (Table 4-6), using Mann Whitney test to compare between the results of sample two and three, where sample two had both dashboard and the traditional financial statements and sample two had the traditional only. It was concluded that there is a significant difference between the two samples with regards to locating the potential fraud since (p-value= .015) which is less than .05. Also, there is a significant difference between the two samples with regards to identifying the potential fraud magnitude since (p-value= .011) which is less than .05. And finally, there is a significant difference between the two samples with regards to the time to locating the potential fraud since (p-value= .002) which is less than .05. Thus, it can be concluded that there is significant difference between sample two using both dashboard and the traditional financial statements, and sample three using traditional financial statements with regards the three research variables.

Table 4- 6: Comparison 3

	Locate Potential Fraud	Potential Fraud Magnitude	Time in Seconds
Mann-Whitney U	61.000	58.500	44.500
Wilcoxon W	127.000	124.500	110.500
Z	-2.802	2.803	-3.019
Asymp. Sig. (2-tailed)	.005	.005	.003
Exact Sig.	.015[b]	011[b]	.002[b]

From the above discussion, it can be concluded that there is significant difference between sample 1 and sample 3, thus using dashboards significantly impacted respondents' performance with regards to locating the potential fraud, potential fraud magnitude and in better time than using traditional financial statements only. Those results are consistent with prior literature (Collaris et al., 2018; Hoelscher & Mortimer, 2018; Morar et al., 2019). Thus, the three research hypotheses were supports as such:

*H1: There is a significant difference between dashboard and traditional accounting in detection the potential fraud location, **which is supported.***

*H2 There is a significant difference between dashboards and traditional accounting in detection the potential fraud magnitude, **which is supported.***

*H3: There is a significant difference in time between dashboards and traditional accounting in detecting the potential fraud, **which is supported.***

4.4 Additional Analysis

Further analysis was conducted to examine the impact of the three control variables: gender, CGPA and experience with dashboard. The following section is divided into three subsections: section one discussed the impact of gender, section two discussed CGPA impact and finally, section three discussed the experience impact.

4.4.1 Gender Effect:

In the stage of determining whether gender has an impact on the results, how to extract the data, and whether the person has experience with dashboard or not, in this step we present the statistics based on the experiment that we did on a group of students between males and females, and the results were as follows, There was insignificant weak correlation found between gender which indicates that males had no more experiences than females with the dashboard and vice versa as p-value = $0.955^b > 0.05$, and also there was no difference in the preference of one of the genders in locating the potential fraud (p-value = 1.000^b), and therefore there was no difference in knowing the potential fraud correctly (p-value = 0.955^b).

Table 4- 7: Gender Effect

	Locate Potential Fraud	Potential Fraud
Mann-Whitney U	28.000	27.500
Wilcoxon W	64.000	63.500
Z	0.000	.098
Asymp. Sig.	1.000	.922
Exact Sig.	1.000^b	$.955^b$

4.4.2 CGPA Effect

Next comes the CGPA in the role of determining whether it has an impact on the results, where the experiment was conducted on a group of students with diversity in terms of CGPA to see if the individual with high CGPA has more positive results in terms of locating the potential fraud or that the potential fraud is correctly extracted, and whether that the person extracted the potential fraud in a small record time and the results were as follows, There was insignificant weak correlation found between students with high CGPA and students with low CGPA in terms of locating the potential fraud as p-value = 1.000 > 0.05, and also there was no difference in knowing the potential fraud correctly (p-value = 0.478), and the difference in the time taken to locate the potential fraud was not significant among the students (p-value = 0.240)

Table 4- 8: CGPA Effect

	Locate potential Fraud	Potential Fraud	Time in Seconds
Chi-Square	.000	3.500	5.493
df	4	4	4
Asymp. Sig.	1.000	.478	.240

As per the previously supplied statistical explanation, the experiment yielded data that corroborate the idea that gender has no bearing on an individual's higher CGPA. These findings support the validity of the impact of the independent variable under investigation—the dashboard as opposed to conventional financial reports—on the possibility of detecting fraud.

5. Conclusion

As Accounting Information systems are becoming more complicated, fraudsters are coming up with new ways to commit fraud and are creating sophisticated strategies to get around system controls that have been put in place. In addition to, the complexity of these frauds and other "white-collar" crimes, new perspectives are needed in order to properly analyze and make use of the vast amounts of data that are being generated. Besides, in an accounting information system, thousands of transactions every day produce thousands of lines of data. There might be fraudulent transactions concealed within these gigabytes of data that are really difficult to find. It is the duty of auditors and forensic analysts to look for fresh and creative ways to identify fraud. It is difficult to detect complete fraud, and there is no "magic bullet" that can guarantee it. When paired with other methods, visualization can help auditors spot questionable activity that might otherwise go unnoticed and inspire additional research. The insights gained from this study offer fresh motivation for visualization research. It is recommended that more research be done on using these approaches to identify other fraud schemes and investigating other cutting-edge visualization techniques. Information provided as visuals rather than text is processed by the human eye more quickly. Our inherent ability to handle complicated concepts through visual identification develops with time.

The objective of this research is to investigate the impact of using BI namely dashboards based BI on the potential fraud detection by auditors. Based on a sample of 49 auditors proxied by E-JUST fourth year students, the results revealed a significant difference between using dashboards and traditional methods for fraud detection by auditors where using dashboard is more timely and more accurate with regards to locating the potential fraud and the magnitude of the potential fraud. **This research contributes to prior literature** by providing evidence on the explicit use of dashboards in fraud detection by auditors. Also, this research helps achieve these goals by investigating how information relates to various choice tasks and how "source variability," or the dependability of graphical recommendations, can affect user performance. Also, this research contributes to the profession by providing insights on how auditing professionals can embrace big data, data analytics, and artificial intelligence (AI) to stay ahead of the competition and take advantage of many opportunities in this quickly changing, disruptive, but ultimately beneficial environment.

The author acknowledges the following limitation regarding generalizability of results from this research. First, to prevent users from mistakenly seeing trends in the data, dashboards—which are high-level summaries of the data—should help users comprehend the variability in the source data and point them toward more pertinent information. Second, as the focus of this study is financial statement fraud, care must be taken when extrapolating these results to other fraud categories, such accounts receivable. Third, the examination of the findings will offer more information that could be helpful in enhancing the evidence, regardless of whether the suspicious activities prove to be possible frauds, frauds, or regular transactions. Fourth, only one tool of the big data tools is implemented which is Microsoft power BI which limits the scope of the research. Finally, data quality should not be taken for granted as it might significantly affect the explanation. **Those limitations provide sufficient directions for further study,** to investigate the impact of different visualization tools on other tasks performed by the auditor other that fraud detection. Also, more research might examine the decision-making processes that users of dashboards go through, especially in situations when the dashboard appears to be intended to facilitate quick, intuitive decision-making. Finally, to find out how auditing experts strike a balance between using traditional tools and data analytics tools, more research is required.

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