Big Data Analytics and Firm Performance: An Empirical Investigation of Direct and Mediating Effects

Prepared

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Abstract:

The development of cloud computing, the internet of things and social media has increased the volume of data, which cannot be stored or analyzed by traditional data analytics techniques. Therefore, big data analytics has become an essential tool for dealing with big data. This study examined the relationship between big data analytics and both market and financial performance, with the mediating effect of strategic decision quality. Based on 150 observations of Egyptian banks that use BDA and those that do not use BDA. The results showed that strategic decision quality, financial, and market performance had been improved because of the adoption of BDA. In addition, the financial and market performance were higher after the adoption of BDA than before the adoption of BDA. They were also higher for the banks that use BDA than those that do not use BDA. Finally, the results indicated that strategic decision quality has a mediating effect on the relationship between BDA and firm performance.

Keywords: big data, big data analytics, financial performance, market performance, strategic decision quality.

I. Introduction

Data is the raw material of the 21st century (Elgendy and Elragal 2016). It is considered the main factor for making decisions, establishing competitive advantages, and increasing the business value (Lee at el. 2017). In addition, the developments of information and communication technology (ICT), the emergence of E-commerce, Electronic Data Interchange (EDI), cloud computing, and the Internet of Things (IoT) have introduced a large volume of data (Tan et al. 2017; Ferraris et al. 2019; Li and Liu 2020). Big data refers to the complex amount of data that cannot be stored, processed, and analyzed by a database system or traditional data processing application (Salwan and Maan 2020; Casarotto et al. 2021). Due to the big data, the semi-structured and unstructured data have been increased and the traditional data analytics tools cannot analyze those types of data (Lee at el. 2017).

Therefore, big data analytics (BDA) is used now more and more as an effective way to generate real-time and valuable information from a large amount of data (Elgendy and Elragal 2016; Thirathon et al. 2017; Singh and El-Kassar 2019). It is an emerging technology for managing, processing, and analyzing five dimensions of large volumes of data, which are volume, variety, velocity, veracity, and value to provide valuable information for decision-makers (Wamba et al. 2017; Popovič et al. 2018; Sagi and Jain 2018). BDA helps managers to generate real-time and useful information from the huge amount of data and transfer the information generated into accurate decisions, which enhance customers relationship, establish competitive advantages, manage the operational risks, and improve the overall firm performance (Wamba et al. 2017; Ferraris et al. 2018; Wamba et al. 2019).

Furthermore, BDA provides several benefits for firms like fraud detection, cost and time saving, and the creation of new products or services (Balachandran and Prasad 2017; Jeble et al. 2017; Nawaz 2020). In addition, it provides faster and better decision-making, and higher customer retention by collecting data about customer needs, and preferences (Balachandran and Prasad 2017; Jeble et al. 2017; Nawaz 2020). Therefore, the effective use of BDA can improve firm's strategies, visions and plans, services and products quality, customer relationship management, and competitive advantages (Huifen and Jifan. 2018).

Despite the many advantages that firms can gain from investing in BDA, there is a scarcity of studies addressing the relationship between BDA and firm performance and how firms can gain competitive advantages through investment in BDA. In addition, there is a limited understanding of the information quality that can be provided by depending on BDA and how to use this information in making accurate decisions that lead to improving the firm's profitability, sales growth, return on investment, and stock market return.

Furthermore, most previous studies that investigated the relationship between BDA and firm performance depended on the indirect effect of BDA on firm performance, for example, Muller et al. (2018) examined the indirect effect of industry characteristics on the relationship between BDA and firm performance. While others depended on the indirect effect of knowledge management on the relationship between BDA and firm performance (Ferraris et al. 2018; Nawaz 2020). Moreover, Raguseo and Vitari (2018) investigated the mediating effect of customer satisfaction and market performance on that relationship. Similarly, Wamba et al. (2018) examined the indirect effect of user satisfaction and business value on that relationship.

In addition, the dynamic and operational capabilities of BDA play an important role in improving the firm performance (Mikalef et al. 2020). Furthermore, most previous studies have focused on financial performance, ignoring the impact of BDA investment on firms' market performance. Therefore, this research is trying to extend the previous studies by examining the direct and indirect effect of BDA on firm performance, which is one of the most critical success factors for firms (Janssen et al. 2017; Polese et al. 2019). Previous studies showed that BDA can improve firm performance by improving the firms' ability to retain customers, open new markets more quickly than their competitors, and provide new products or services (Ren et al. 2017; Mikalef et al. 2019).

On the other hand, BDA provides accurate information for decision-makers, which helps them identify their customers' needs, and increase their satisfaction (Raguseo and Vitari 2018). In addition to making efficient strategic and operational decisions, which in return improve firms' profitability, sales growth, and return on investment (Thirathon et al. 2017). Therefore, the objectives of this research are as follows: first, it empirically tests the effect of BDA on the quality of strategic decisions. Second, it examines the effect of BDA on both financial and market performance. Third, it aims to identify the difference in firm performance before and after using

BDA and between the companies that use BDA and those that do not use BDA. Finally, it aims at understanding if strategic decision quality mediates the relationship between BDA and firm performance. The remainder of this paper is organized as follows: the next section focuses on the theoretical background followed by the literature review and hypothesis development, then the research methodology is explained followed by the research results. The last section focuses on the study's conclusion, its implications, limitation, and suggestion for future research.

II. Theoretical Background

Big data refers to a huge amount of data that cannot be stored, processed, and analyzed using database systems or traditional data processing applications (Thirathon et al. 2017; Jeble et al. 2017; Ferraris et al. 2019; Nawaz 2020). It has five characteristics (5Vs), which are volume, variety, velocity, veracity, and value (Jeble et al. 2017; Ferraris et al. 2019; Nawaz 2020; Casarotto et al. 2021). Figure 1 shows the 5Vs of big data.

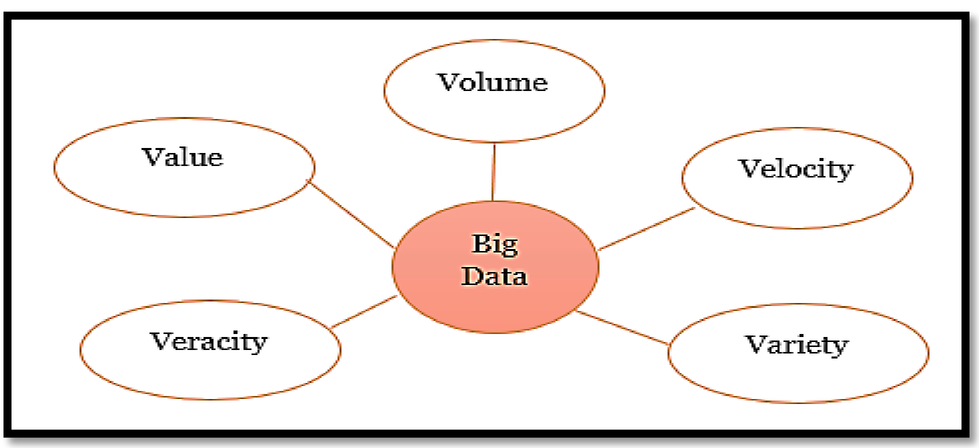

Figure 1:the 5Vs big data characteristics
(Source: The researcher)

1. Volume: it refers to the massive amount of data generated every day and every minute by humans and by machines from different digital sources (Jeble et al. 2017; Casarotto et al. 2021). That amount of data generated is larger than the internet storage capacity, so the traditional systems cannot handle it (Thirathon et al. 2017; Saggi and Jain 2018; Nawaz 2020).
2. Variety: it refers to the various data types collected from different digital resources (Jeble et al. 2017; Ferraris et al. 2019). Big data has three different types, which are structured data, unstructured data, and semi-structured data (Thirathon et al. 2017; Casarotto et al. 2021).

   The structured data represents 20% of the existing data, and it can be stored, processed, and analyzed in a rational database system (Thirathon et al. 2017; Casarotto et al. 2021). This is because it includes all data generated by humans and machines such as personal details, GPS data, and medical devices' data, which have a fixed format like excel or word file (Thirathon et al. 2017; Casarotto et al. 2021).

   The unstructured data represents 80% of the existing data, and it cannot be stored, processed, or analyzed by a relational database (Thirathon et al. 2017; Saggi and Jain 2018; Casarotto et al. 2021). This is because it does not have a certain format, and it includes social media data, website content, and mobile data, so all videos, images, emails, and audios are classified as unstructured data (Thirathon et al. 2017; Saggi and Jain 2018; Casarotto et al. 2021). The semi-structured data is the data that is not in the traditional database but contains some organizational properties such as elements and tags in XML and HTML files, which make it easier to process (Thirathon et al. 2017; Casarotto et al. 2021).

3. Velocity: it refers to the high speed of data generated from different resources like mobile devices, laptops, tablets, and more (Saggi and Jain 2018; Casarotto et al. 2021). The speed of data is the main success factor in business because it allows the decision-makers to be more agile and faster in making decisions than their competitors (Jeble et al. 2017; Ferraris et al. 2019; Samsudeen 2020).

4. Veracity: the data collected by different digital sources are incomplete, uncertain, and noisy, so it needs a huge amount of processing (Thirathon et al. 2017; Ferraris et al. 2019), to be accurate, complete, and trusted for decision-making purposes (Jeble et al. 2017; Nawaz 2020).

5. Value: it refers to the results of big data processing that enable firms to detect fraud, manage the risks, develop new products, and make better decisions (Ferraris et al. 2019; Nawaz 2020; Casarotto et al. 2021).

Traditional data analytics like UNIX are not efficient for storing and analyzing a large amount of data by using a single machine (Salwan and Maan 2020). Therefore, big data analytics (BDA) tools like Hadoop and Apache Spark are used to store and process big data (Elgendy and Elragal 2016; Thirathon et al. 2017; Mikalef et al. 2019). This is because they depend on distributed storage, and parallel processing (Elgendy and Elragal 2016; Thirathon et al. 2017; Mikalef et al. 2019). Thus, they can process every type of data, which allows users to generate real-time and useful information from the huge amount of data (Elgendy and Elragal 2016; Thirathon et al. 2017; Mikalef et al. 2019).

BDA is a new technology for managing, processing, and analyzing the five dimensions of big data to extract valuable information from a large volume and a broad variety of data (Côrte-Real et al. 2017; Mikalef et al. 2020; Nawaz 2020). It is also a tool for acquiring effective insights, such as hidden patterns, unknown correlations, market trends, and customer preferences to develop business value and create competitive advantages (Raguseo and Vitari 2018; Ferraris et al. 2019;Wamba et al. 2019).

The analytics of big data can be classified into four main types, which are descriptive, diagnostic, predictive, and prescriptive (Mohammed et al. 2014; Jeble et al. 2017; Thirathon et al. 2017). Figure 2 shows the types of big data analytics.

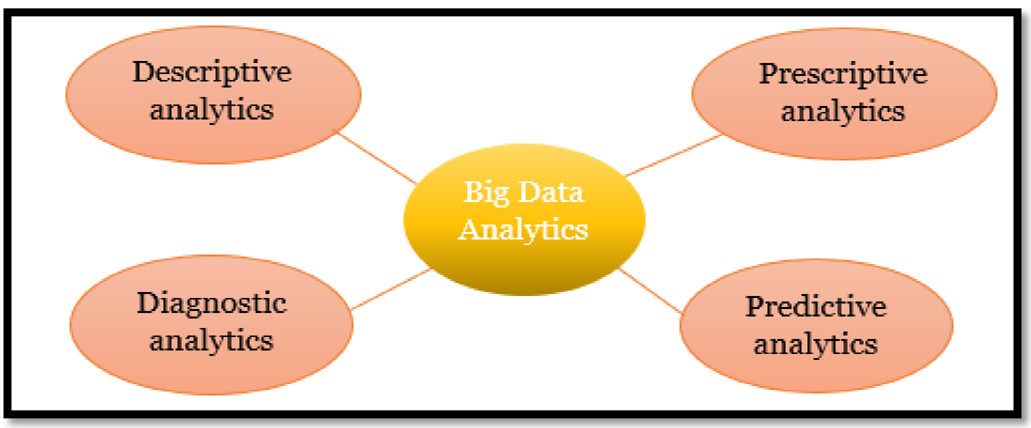

Figure 2: Big data analytics types
(Source: The researcher)

Descriptive analytics explains what happened in the past based on data presented through graphics and reports (Rozados and Tjahjono 2014). It depends on historical data to discover models that can help managers understand what happened in the past and make precise managerial decisions, for example, companies can review its performance by analyzing its revenues over the years (Thirathon et al. 2017; Saggi and Jain 2018). Therefore, those analytics are used for creating various reports like a firm's revenue, profit, and sales (Sheng et al. 2020).

Diagnostic analytics, explains why any problem has occurred, so it depends on various techniques like drill-down, data mining, and data discovery to investigate the cause and effect of any past problem (Baum et al. 2018) and understand why it has occurred and arrived at a particular solution for it (Rozados and Tjahjono 2014). Predictive analytics depends on the historical data and the relationship between data to make predictions of the future (Mohammed et al. 2014; Jeble et al. 2017; Thirathon et al. 2017; Baum et al. 2018). So, it uses some techniques like artificial intelligence, data mining, and machine learning to predict customer trends and behavior, and market trends (Rozados and Tjahjono 2014; Sheng et al. 2020).

Prescriptive analysis works with descriptive and predictive analytics and relies on artificial intelligence and machine learning to prescribe a solution to a certain problem (Rozados and Tjahjono 2014; Sheng et al. 2020). It uses optimization and simulation algorithms to provide users with different possible actions and guides them toward the best solution (Mohammed et al. 2014; Jeble et al. 2017; Baum et al. 2018). In addition, two tools can be used in big data analytics, which are Hadoop and Apache Spark (Verma et al. 2015; Sethy and Panda 2015; Mătăcuţă and Popa 2018). Hadoop is widely used for storing and analyzing data across different computers (Ferraris et al. 2019; Wamba et al. 2019). It is a framework for managing big data, storing it in a distrusted way, and processing it in a parallel fashion (Verma et al. 2015; Sethy and Panda. 2015; Mătăcuţă and Popa. 2018).

Hadoop consists of three components that were specifically designed to work on big data (Sethy and Panda 2015). The first component is Hadoop distributed file system (HDFS) distributes the massive data amongst many computers and stores it in blocks, which are replicated amongst different data nodes (Mătăcuţă and Popa 2018). Therefore, when any data block is created it is replicated and stored on different data nodes this is termed the replication method (Mohammed et al. 2014; Sethy and Panda 2015; Mătăcuţă and Popa 2018). Figure 3 shows an example of HDFS

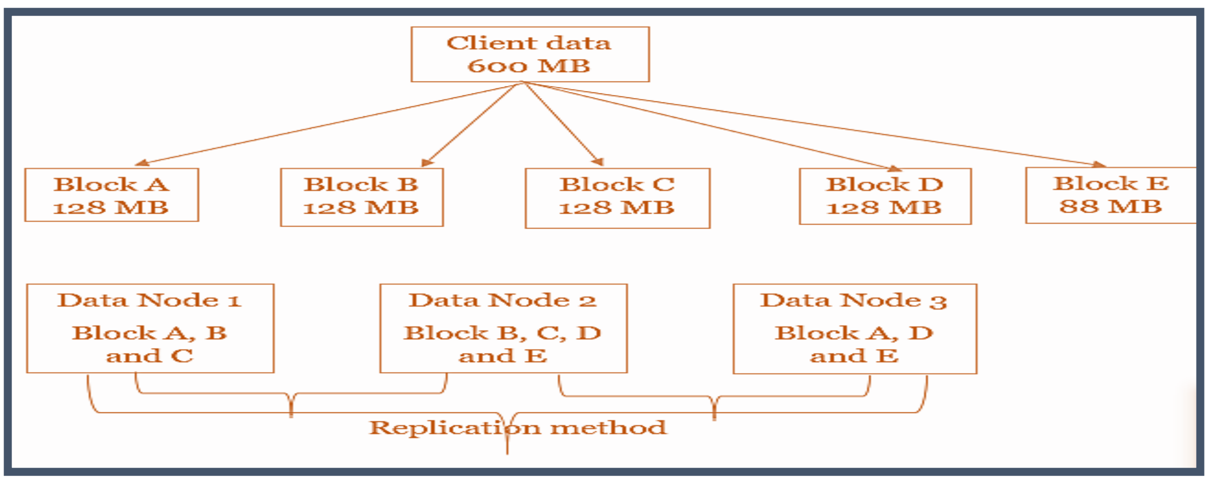

Figure 3: Hadoop Distributed File System (HDFS)
(Source: The researcher)

The second component of Hadoop is MapReduce, which is a programming technique for processing a huge amount of data in a distributed and parallel way (Mohammed et al. 2014; Sethy and Panda. 2015; Ghazi and Gangodkar 2015). It splits data into parts and processes each of them separately on different data nodes, then the results are aggregated and sent to the master node to give the final output (Mohammed et al. 2014; Sethy and Panda. 2015; Maitrey and Jha 2015).Figure 4 shows an example of Hadoop MapReduce.

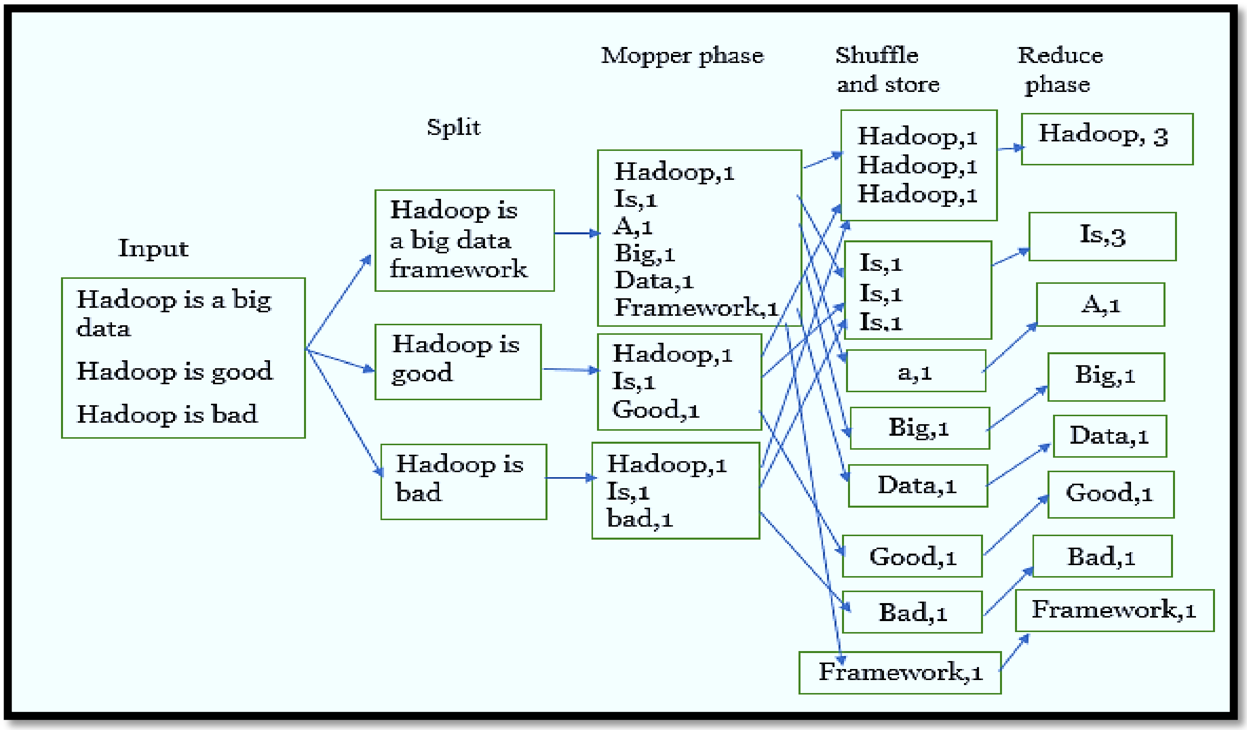

Figure 4: Hadoop MapReduce

(Source: The researcher)

The third component of Hadoop is yarn (yet another resource negotiator), which is a processes job that requests and manages cluster resources in Hadoop (Mohammed et al. 2014; Sethy and Panda. 2015). It consists of a resource manager, node manager, and application master (Mohammed et al. 2014; Perwej et al. 2017; Mătăcuţă and Popa. 2018). A resource manager is responsible for resource allocation and management, while the node manager manages the nodes and monitors resource usage (Perwej et al. 2017). The application master requests containers from the node manager (Perwej et al. 2017; Mătăcuţă and Popa. 2018). The container is a collection of physical resources like RAM and CPU (Mohammed et al. 2014; Perwej et al. 2017; Mătăcuţă and Popa. 2018).

Apache Spark is another tool for analyzing big data, which provides faster processing at a lower time than Hadoop (Salwan and Maan 2020). It emerged after Hadoop's MapReduce as an open-source framework for data processing in the main memory of the data node (Salloum et al. 2016). Therefore, it prevents unnecessary input/output overhead and provides support to various development languages like Java, Scala, and Python (Salloum et al. 2016).

Spark consists of several components, the first component is Spark Core, and Resilient Distributed Data sets (RDD's) (Bansod 2015; Shoro and Soomro 2015). The Spark Core represents the foundation of the entire spark project, and it provides basic input/output functionalities distributed tasks dispatching and scheduling (Bansod 2015; Salloum et al. 2016). The Resilient Distributed Data sets are the basic programming abstraction and are a collection of data that is partitioned across machines (Bansod 2015; Salloum et al. 2016). The second component is Spark SQL, which introduces schema RDD, which is a new data abstraction and supports semi-structured and structured data (Bansod 2015; Shoro and Soomro 2015). The third component is spark streaming, which leverages the fast-scheduling capability of spark core for streaming analytics ingesting data in small batches, and performing RDD transformations on them (Bansod 2015; Shoro and Soomro 2015). The fourth component is Machine Learning Library (MLlib), which is a distributed machine learning framework that applies various common statistical and machine learning algorithms with its memory-based architecture (Bansod 2015; Shoro and Soomro 2015; Salloum et al. 2016). The last component of Spark is GraphX, which distributes a graph processing framework for the computation of graphs (Bansod 2015; Shoro and Soomro 2015; Salloum et al. 2016). Figure 5 shows Spark components.

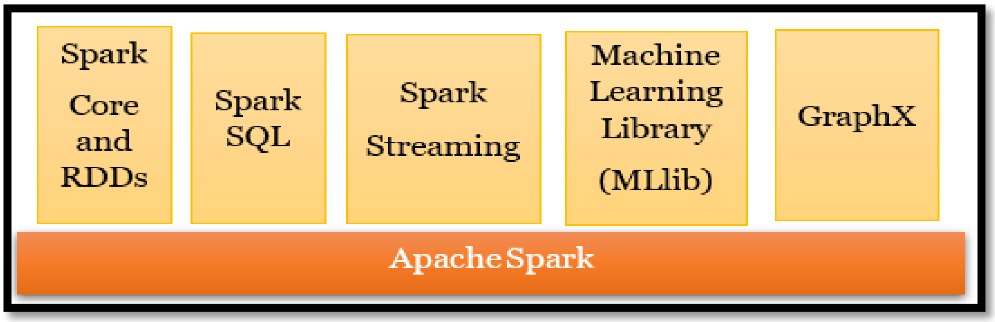

Figure 5: Apache Spark Components
(Source: The researcher)

III. Literature Review and Hypotheses Development

BDA provides complete, accurate, updated, and real-time information in the proper form to managers to help in operational management. It also helps firms reduce operating costs, employee productivity, and product innovations. In addition, it improves the firm's ability to identify customers' needs, which reduces costs, enhances customer satisfaction, and firms' competitive advantages, which enhances the overall firm performance. Several studies have examined the relationship between BDA, managerial decisions, competitive advantages, and firm performance. They identified how BDA investment can help managers to extract and generate useful information and knowledge and depend on it to know more about their business and transfer the knowledge generated into efficient decisions.

BDA and decision-making process:

New managerial and executive decisions can be made by using BDA; therefore, several authors have discussed the positive relationship between BDA and the decision-making process. For example, Jeble et al. (2017) showed that BDA helps managers in making accurate decisions by providing information about products that can be bought together, and items that their demand will be increased. It also provides them with real-time information, which allowed them to act faster than their competitors. As shown by Ren et al. (2017), BDA system quality like integration, accessibility, privacy, and reliability improved the information quality by providing complete and accurate information. The quality of information helped managers make good decisions, which improved the firm value and financial performance. Similarly, a study by Samsudeen (2020) found that BDA allowed managers to convert their knowledge into valuable decisions and predict their business future performance, which improved their decisions and overall effective decision-making process. Based on the previous studies, BDA provides managers with valuable information, which helps them predict the future, reduce risks and uncertainty, acquire new customers, initiate new products, services, or markets, and gain more chances. This leads to the following hypothesis:

H1: BDA has a significant positive effect on strategic decisions quality.

BDA and firms' performance.

The investment in BDA can improve the market value of the firm because that investment will be reflected in the stock price. Accordingly, Lee et al. (2017) used an event study to examine the relationship between stock price and the announcement of the BDA. They found that the announcement of BDA investment increases the stock market reactions, which are bigger for the big firms than the small firms. Côrte-Real et al. (2017) investigated the positive association between BDA and business value. BDA was found to have a positive effect on firms’ agility by improving knowledge management, competitive advantages, and performance. Agility also was found to have a mediating effect on the relationship between managers’ knowledge and firm performance.

On the other hand, BDA improves the firms' dynamic capabilities by improving their ability to sense and respond quickly to any changes in the market. It also helps them identify opportunities and threats, and preserve competitiveness by improving and protecting the operational, marketing, and technology capabilities. Thus, Wamba et al. (2017) investigated the mediating effect of dynamic capabilities on the relationship between BDA and firm performance. Based on a survey of 297 Chinese IT managers and business analysts. The results indicated that BDA capabilities have a higher positive impact on firm performance than dynamic capabilities because the three types of BDA capabilities are linked together to improve the firm performance. The results also revealed that the infrastructure and personal capabilities of BDA improve the firm performance more than the management's capabilities. This is because technology and people are important to developing analytics models and managing and analyzing data.

Similarly, Huifen and Jifan (2018) examined the moderating effect of a dynamic environment on the relationship between BDA and firm performance. BDA usages were found to provide dynamic capabilities that helped in developing decisions making, competitive advantages, and performance. Moreover, BDA improves the collection and efficient distribution of data that can be used in making precise decisions within the organization. In addition, the strong competition between firms increases the use of BDA, which increases the firm value. Therefore, Muller et al. (2018)

examined the moderating effect of industry competitiveness on the relationship between BDA and firm productivity. The results showed that BDA investment explains 7% of firm productivity. The value that can be extracted from the investment in BDA is higher for information technology firms and highly competitive industries. In addition, Raguseo and Vitari (2018) examined the direct and indirect effects of BDA investment and firm performance, mediated by customer satisfaction and market performance. The authors surveyed 200 medium-sized and large French companies. The results showed that BDA increases customer satisfaction by improving the understanding of what customers want. It also improves the firms' ability to provide new products or services and reach new markets faster than their competitors, which improved firms' financial performance.

On the other hand, many authors have discussed the positive relationship between BDA and firm performance, mediated by knowledge management. For example, Ferraris et al. (2019) examined the mediating effect of knowledge management on the relationship between BDA capabilities and firm performance. They concluded that firms that depend on BDA capabilities, their profitability, sales growth, return on investment, and customer retention have been increased than the other firms that do not depend on BDA capabilities. They also found that BDA increased the ability of managers to generate new knowledge and use the data generated to increase customer satisfaction and stock price. Similarly, Newaz (2020) investigated the relationship between BDA and firm performance mediated by knowledge management. He concluded that BDA improved the firm performance by improving the inclusion, processing, and utilization of data derived from

BDA. Yasmin et al. (2020) concluded that the combination of BDA capabilities such as technology, management, and talent capabilities has achieved goals, competitive advantages, and improved performance.

Taken together, the previous studies outlined above suggest that BDA provides managers with valuable information, which helps them predict the future, reduce risks and uncertainty, acquire new customers, and gain more chances. It also helps them to make accurate decisions. This is because they depend on it to know more about their business and transfer the knowledge generated into efficient decisions, which reduce firms' operating and communication costs. It also increases firms' agility to act faster as the environment changes than their competitors and establishes competitive advantages. In addition, BDA provides valuable information to understand customers’ needs, introduce new products or services, develop visions, and create new plans. This lead to improve user and customer satisfaction, stock market return, firms’ sales, profitability, return on investment, future cash flow, and overall performance. Therefore, the second research hypothesis is as follows

H2: BDA has a significant positive effect on firm performance.

Additionally, previous studies agreed on BDA investment increases the information quality, which helps managers in making accurate strategic and operational decisions. That leads to improve the firms' return on assets, return on equity, return on investment, and sales rate. This leads to the following hypothesis:

H2.a: BDA has a significant positive impact on firms' financial performance.

Furthermore, the investment in BDA will cause a change in the stock market return because investors evaluate the benefits, efficient decisions, customer satisfaction, and competitive advantages, that the firms can generate from the adoption of BDA. Therefore, the investment in BDA improves firms' stock market return. This leads to the following hypothesis:

H2.b: BDA has a significant positive impact on firms' market performance.

In addition, most previous studies agreed that BDA improves the collection of data and increases its use in the decision-making process. It also improves a firm's ability to gain more customers, and increase its productivity, so firms that adopt BDA their performance is higher than those that do not use BDA. This leads to the following hypotheses:

H2.c: The firm performance is higher after the adoption of BDA than before the adoption.

H2.d: The firm performance of adopting companies is higher than that of non-adopting companies

The mediating effect of strategic decisions quality.

BDA improves firm performance by reducing operating and communication costs, increasing the firm’s returns, improving its relationship with customers, and making new strategic plans (Jeble et al. 2017). Therefore, many authors have investigated the relationship between BDA and firm performance mediated by the decision-making process. For example, Thirathon et al. (2017) investigated the relationship between BDA, decision-making, and firm performance. The results indicated that BDA helps managers in making operational and strategic decisions. It also increases the small firms' ability to compete with large firms. In a similar line, Popovic et al. (2018) found that BDA capabilities helped managers make accurate operational and strategic decisions, which improve the firm performance and its competitive advantages. Furthermore, Huifen and Jifan (2018) examined the moderating effect of a dynamic environment on the relationship between BDA and firm performance. BDA usages were found to provide dynamic capabilities that helped in developing decisions making, competitive advantages, and performance.

On the other hand, BDA helps managers in creating long-term business plans, learning, and creation, and reducing risks, uncertainty, customer gaining costs, and improving their relationship with customers, which improve firm performance. Therefore, Raguseo and Vitari (2018) concluded BDA helps firms identify customer needs, which increases their loyalty and satisfaction, and that in turn increases the cash flows and firm performance. In addition, BDA improves firms' agility to act faster to any changes in the environment, thus, Wamba et al. (2019) explored the mediating effect of user satisfaction and business value on the relationship between information quality in BDA and firm performance. The results revealed that the information quality generated from BDA helps users in reducing operating and communication costs. The authors also concluded that BDA enhances employee productivity, customer relationship, and firms' agility, develops new business plans, and provides better products, which increase user satisfaction, improve business value, and overall firm performance.

The importance of the dynamic and operational capabilities of BDA has been highlighted by Mikalef et al. (2020), which explored the mediating effect of dynamic and operational capabilities on the relationship between BDA capabilities and competitive performance. They found that BDA capabilities, which are tangible like organizational culture and learning, and intangible like employee's skills and knowledge, and physical and financial resources, improve the dynamic capabilities of the firm. They also found that BDA capabilities improve the ability of the firms to sense and understand their customer needs and identify the technology developments and those improve the firms' competitive performance. Furthermore, Bogdan and Borza (2020) indicated that BDA helps firms to provide new products or services, modify their products according to customers' needs, and reduce customer obtaining costs, which improve firm performance.

Based on the previous studies, BDA helps managers make accurate decisions, which reduce a firm’s operating and communication costs, increase its agility to act faster to the environmental changes, establish competitive advantages and improve its performance. Therefore, the ability of users to understand the information generated by BDA and interpret it into efficient managerial decisions can improve firm performance. In addition, BDA helps managers to generate new knowledge and use it to understand customers' needs, expectations, and problems, which increase their loyalty and satisfaction and improve firms' cash flow. This leads to the following hypotheses:

H3: Strategic decision quality has a mediating effect on the relationship between BDA and firm performance.

Based on the previous discussion, the researcher derived the following model:

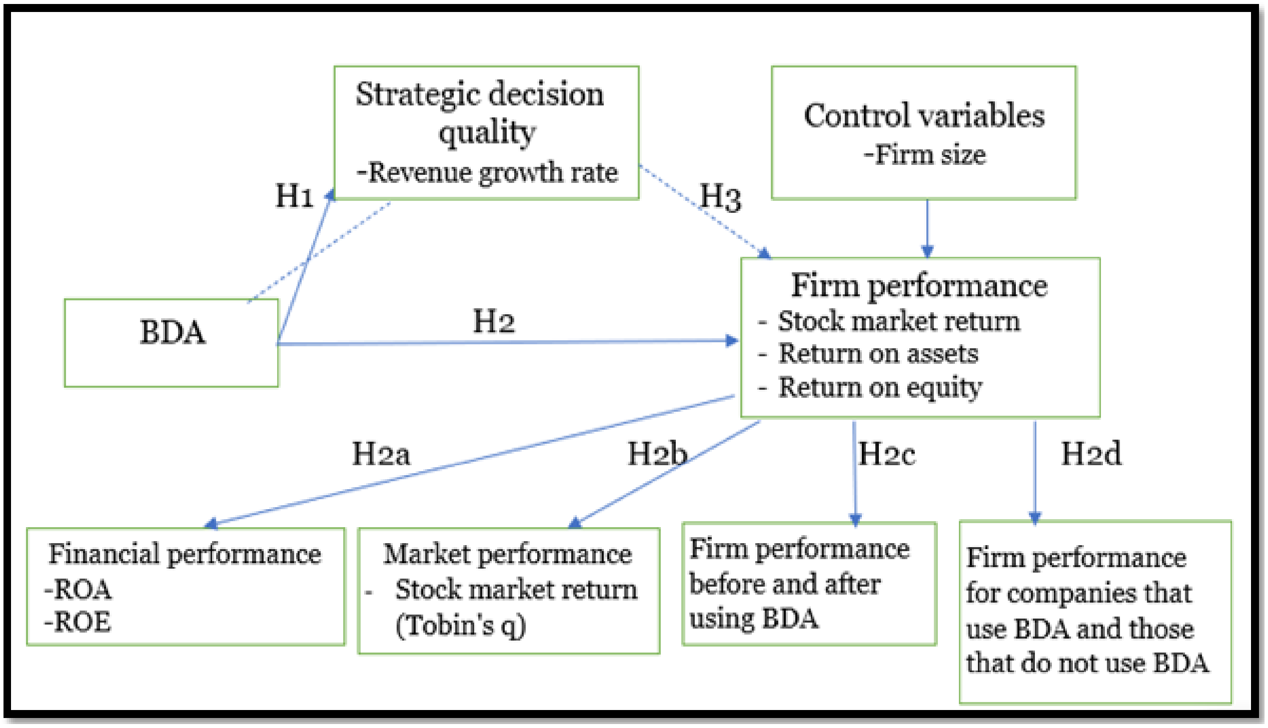

Figure 6: Research Model

IV. Research Methodology

The researcher conducts a review of relevant literature, which constitutes the theoretical foundation for the research, and, in turn, leads to the formulation of research hypotheses that will be tested empirically using a sample of 30 Egyptian banks. Five years period (from January 1st, 2015, to December 31st, 2019), two years before the adoption of BDA, 2015 and 2016, and three years after the adoption of BDA, 2017, 2018, and 2019, so overall (150) firm-year observations were included. Announcement of BDA investment was collected by searching for keywords such as big data analytics, data analytics, business analytics (Lee et al. 2017), Hadoop, Apache spark, mongo, Kafka, Cassandra, and storm. Pre-announcement firms' performance and post-announcement firms' performance will be measured to ensure that the firms' performance has been improved after the adoption of BDA. In addition, the comparison between adopting firms and non-adopting firms will be conducted to compare the financial and market performance of the two groups.

Variable Measurements.

The measurements of the research variables are developed based on previous studies, the dependent variable is firm performance, which refers to firms' ability to anticipate and advance against competitors, gain, and retain customers and improve sales, profitability and return on investment (Thirathon et al. 2017; Raguseo and Vitari. 2018; Huifen and Jifan. 2018; Gupta et al. 2019). It includes both financial and market performance (Raguseo and Vitari. 2018). Financial performance refers to high productivity and profitability, sales and revenue growth, customer retention, and return on investment (Thirathon et al. 2017; Raguseo and Vitari. 2018; Huifen and Jifan. 2018; Gupta et al. 2019). Therefore, it was measured depending on some ratios like return on assets (ROA) and return on equity (ROE). (Thirathon et al. 2017; Gupta et al. 2019). Market performance refers to the firms’ ability to increase their position by providing new products, increasing customers' attention, and acquiring high market value (Thirathon et al. 2017; Raguseo and Vitari. 2018; Huifen and Jifan. 2018; Gupta et al. 2019). Thus, it was measured depending on the stock market return (Tobin's Q).

The independent variable is BDA, which refers to collecting, processing, and analyzing data and providing useful information to decision-makers

(Wamba et al. 2019; Ferraris et al. 2019). It is a binary indicator variable, so it was measured by giving a value of zero in the year preceding the adoption and for companies that do not use BDA and a value of one in the year after the adoption and for the companies that use BDA (Muller et al. 2018). Strategic decision quality was used as mediating variable. The strategic decision includes providing new products or services and opening new market channels (Thirathon et al. 2017). It was measured by the revenue growth rate, which is an indicator of how well a firm can increase its sales revenue over time. Firm size was used as control variable because it may affect the firm performance. Firm size was measured as an ordinal value in accordance with the Central Bank of Egypt classifications of firm size, therefore, value one was used for micro firms (less than 10 employees), value two was used for small and medium firms (from 10 to 200 employees), and value three was used for large firms (more than 200 employees).

V. Research Results.

Descriptive statistic

The descriptive statistics presented in table 1 indicate that all the 150 observations (80 observations for non-adopting firms, 31 observations for firms that use BDA but before the adoption of BDA, and 39 observations for firms that use BDA and after the adoption of BDA).

Table 1.Sample size

Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Total value	150	100.0 %	0	0.0%	150	100.0 %

BDA					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	80	52.6	53.3	53.3
	2	31	20.4	20.7	74.0
	3	39	25.7	26.0	100.0
	Total	150	98.7	100.0	
Missing	System	2	1.3		
Total		152	100.0		

Table 2 shows that 30 firms hired 24,255 employees, on average, the minimum number of employees hired in those firms was 807, and the maximum number of employees was 23,521. The average return on assets of 30 firms was 1.65%, the average return on equity of 30 firms was 15.63%, and the average revenue growth rate of 30 firms was 14.368%.

Table 2. Description of 30 firms

Statistics		
Firm Size		
N	**Valid**	**150**
	Missing	**2**
Mean		**24255**
Median		**4768.00**
Std. Deviation		**58960.454**
Minimum		**807**
Maximum		**23521**

Statistics				
		ROA	**ROE**	**RGR**
N	**Valid**	**150**	**150**	**150**
	Missing	**2**	**2**	**2**
Mean		**1.6581**	**15.6338**	**14.3681**
Median		**1.5700**	**14.3500**	**11.6500**
Std. Deviation		**1.18177**	**14.26332**	**16.97413**
Minimum		**-3.73**	**-55.00**	**-33.00**
Maximum		**5.50**	**58.50**	**63.00**

Test for normality was conducted to indicate the appropriate statistical techniques. Thus, The Kolmogorov-Smirnov test and Shapiro-Wilk test were used to determine whether the data follow the normal distribution or not. The results of the normality test show that all data were normally distributed. This indicates that the observations were drawn from normally distributed populations (p-value = 0.132 and .334), which is greater than 5%, as shown in table 3.Therefore, the parametric statistical techniques(regression, T-test, and Hayes process macro)will be used to test the research hypotheses.

Table 3. Normality test

Tests of Normality						
	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Total	**.139**	**150**	**.132**	**.962**	**150**	**.334**
a. Lilliefors Significance Correction						

Correlation matrix

The Pearson correlation coefficient was used to show the relationship among variables. Table 4showed that there was a positive relationship between the adoption of BDA, ROA, ROE, stock market return, and RGR. Similarly, the result indicated that ROA was positively related to ROE, stock market return, and RGR. The ROE has shown to have a positive relationship with both ROA, stock market return, and revenue growth rate. In addition, there was a significant positive relationship between stock market return, ROA, and ROE. Finally, the revenue growth rate was found to have a significant positive relationship with both ROA and ROE.

Table 4. Correlations

		BDAadoption	ROA	ROE	Tobin's_Q	RGR
BDAadoption	Pearson Correlation	1	.626**	.722**	.743**	.714**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	70	70	70	70	70
ROA	Pearson Correlation	.626**	1	.976**	.968**	.959**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	70	70	70	70	70
ROE	Pearson Correlation	.722**	.976**	1	.986**	.987**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	70	70	70	70	70
Tobin's_Q	Pearson Correlation	.743**	.968**	.986**	1	.975**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	70	70	70	70	70
RGR	Pearson Correlation	.714**	.959**	.987**	.975**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	70	70	70	70	70

****. Correlation is significant at the 0.01 level (2-tailed).**

Regression analysis results

Multiple regression analysis was used to test hypotheses H1, H2, H2a, and H2b and determine the nature of that relationship. The first research hypothesis examined the relationship between the adoption of BDA and strategic decision quality. The results of H1 as shown in table 5, column two, the T-value = 15.89 with P-value <.001, so there was a significant relationship between BDA and strategic decision quality. The adjusted R-square = .680, so 68% of the variance in the quality of the strategic decisions was explained by the changes in the adoption of BDA. The F-value of 159.320 with p-value of 0f .000, indicated a significant positive effect of BDA on the strategic decision quality.

The second research hypothesis examined the relationship between BDA and firm performance. The results in table 5, column three, indicated that the T-value=11.429 with p-value <.001, so there is a significant relationship between BDA adoption and firm performance. In addition, the adjusted R-square =.529, which indicated that 53% of the changes in the firm performance were explained by the adoption of BDA. The F-value of 84.550 with p-value of 0f .000, indicated a significant positive effect of BDA on the firm performance, therefore, H2 was supported.

Furthermore, H2a examined the relationship between BDA adoption and financial performance. The results in table 5, column four T-value = 10.877, with P-value=.000, which indicated that there was a significant relationship between BDA and financial performance. In addition, the BDA explained 51% of the variance in the financial performance, adjusted R-square

=.506. To determine the nature of that relationship, the F-value of 77.355 with p-value of .000, indicated a significant positive effect of BDA on the financial performance.

The results of H2b were presented in table 5, column five showed that T-value was (12.362),and the p-value was less than .001, which indicated a significant relationship between BDA and firms' market performance. Moreover, the adjusted R-square was (.544) and this indicated that 54% of the variance in the market firm performance was explained by the adoption of BDA. In addition, the results indicated a significant positive relationship between the BDA and market firm performance, F-value (89.801) with P-value (.000).Therefore, H2b was supported.

Table 5. Regression Results.

Independent Variables	H1 dependent variable is strategic decision quality	H2 dependent variable is firm performance	H2a dependent variable is financial performance	H2b dependent variable is market performance
Big data analytics T-value Sig	 15.89 .000	 11.429 .000	 10.877 .000	 12.362 .000
Firm size T-value Sig	 1.62 .107	 1.595 .134	 1.554 .122	 .205 .838
Adjusted R-squared	.680	.529	.506	.544
F-statistics Sig	159.320 .000	84.550 .000	77.355 .000	89.801 .000

T-test analysis results

A paired-samples t-test was conducted to examine the H2c and to evaluate the impact of BDA adoption on firms' performance by comparing the firms' performance before and after the adoption of BDA. The results in table 6 showed a significant increase in the firm performance after the adoption of BDA (M=234.1781, SD= 113.31455) to before the adoption of BDA (M= 56.26, SD=26.689), T (30) =-11.279, p=.000 (two-tailed). The mean increase in the adoption of BDA was 177.91817 with a 95% confidence interval, ranging from -210.13 to -145.704.Therefore, hypothesis 2cwas supported.

Table6. Paired samples T-test

Paired Samples Statistics					
		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Before adoption	56.2600	31	26.11213	4.68988
	After adoption	234.1781	31	113.31455	20.35189

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Before adoption - After adoption	-177.918	87.824	15.77366	-210.132	-145.70406	-11.279	30	.000

In addition, independent samples t-test was used to examine the H2d and to compare the firm performance of the companies that use BDA and those that do not use BDA. As presented in table 7, the results reported significant differences between the two groups (t(38.131) = -.988, p=<.001. The firm performance of the companies that use BDA was higher with a mean (M=318.66, SD=214.98) than that of the companies that do not use BDA (M=8.98, SD=12.78). The magnitude of the differences in the means (mean difference= 309.672 with 95% confidence interval, ranging from -379.413 to -239.930, was significant. Hence, H2d was supported.

Table 7. Independent samples t-test

Group Statistics					
	BDAadoption	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**
FP	**1**	**80**	**8.9882**	**12.78525**	**1.42943**
	3	**39**	**318.6603**	**214.98204**	**34.42468**

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
FP	Equal variances assumed	102.585	<.001	-12.895	117	<.001	<.001	-309.67202	24.01530	-357.23306	-262.11097
	Equal variances not assumed			-8.988	38.131	<.001	<.001	-309.67202	34.45434	-379.41331	-239.93072

Mediating analysis results

To test the mediating effect of strategic decision quality on the relationship between BDA and firm performance, Hayes process macro was used to measure the indirect effect on 5000 bootstrap samples at a 95% confidence interval. As presented in table 8 the BDA was statistically significant concerning the quality of the strategic decisions (a=20.24, SE=2.40, p-value=.000), whereas there was a statistically significant relationship between strategic decision quality and firm performance (b=15.2, SE=.67, p-value=.000), and there was a statistically significant relationship between BDA and firm performance (c=262.4, SE=38.84, p-value= .000). The mediating effect of strategic decision quality on the relationship between BDA and firm performance was statistically significant (c`=262.4, SE=38.89, p-value=.000). The indirect effect of ab was above zero (215.41 to 411.34) and was statistically significant, the p-value was less than .01. Thus, hypothesis 3 was supported.

Table 8. Mediating effect results

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : FP
    X  : BDA
    M  : RGR

Sample
Size:  70

**************************************************************************
OUTCOME VARIABLE:
 RGR

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7145      .5105    99.8033    70.9075     1.0000    68.0000      .0000

Model
              coeff         se          t          p
constant    24.3428     6.2619     3.8874      .0002
BDA         20.2420     2.4039     8.4207      .0000
```

```
OUTCOME VARIABLE:
 FP

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .9645      .9303  3084.3851   447.2956     2.0000    67.0000      .0000

Model
              coeff         se          t          p
constant    98.2852    38.4854     2.5538      .0129
BDA         45.4824    19.0998     2.3813      .0201
RGR         15.2101      .6742    22.5618      .0000
```

```
OUTCOME VARIABLE:
 FP

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6332      .4010 26128.1158    45.5144     1.0000    68.0000      .0000

Model
              coeff         se          t          p
constant   468.5406   101.3183     4.6244      .0000
BDA        262.4003    38.8947     6.7464      .0000
```

```
Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
   262.4003    38.8947     6.7464      .0000   184.7869   340.0137     1.2656
```

```
Indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
RGR    307.8827    49.6624   215.4185   411.3460

Partially standardized indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
RGR      1.4850      .0887     1.3405     1.6921
```

VI. Conclusion, Implications, Limitation, and Future Research.

The main objective of this study was to examine the impact of BDA on both market and financial performance, mediated by the quality of the strategic decisions. The results indicated that the quality of the strategic decisions has been improved after the adoption of BDA, which explained 68% of the variance in the quality of the strategic decisions. In addition, the results showed that the BDA had a significant positive impact on firm performance. It has been found to explain 51% of the variance of financial performance, and 55% of the variance of market performance. Moreover, the findings showed that the improvement in the financial and market performance was higher for firms that depend on BDA and after the adoption of BDA than the firms that do not use BDA and before the use of BDA. Furthermore, the relationship between BDA and firm performance was mediated by the quality of the strategic decisions. The mediating effect of strategic decisions quality on the relationship between BDA was (c`=262.4, SE=38.89, p-value=.000).

This study contributes to the existing literature by examining the mediating effect of strategic decision quality on the relationship between BDA and firm performance. Previous studies have not shown whether the quality of the strategic decisions mediates the relationship between BDA and firm performance. Results from this study suggest that the BDA improves strategic decision quality and firms' market and financial performance. In addition, the quality of the strategic decisions mediates the relationship between BDA and firm performance. Additionally, the importance of the examination of the impact of BDA on managerial decisions is magnified with the emphasis on the importance of information in terms of its relevance, reliability, and comparability to the decision-makers, on which he/she depends to make accurate decisions.

Although some previous studies have examined the impact of BDA on firm performance, this research is the first that investigates the impact of BDA on firm performance for two samples, the first one is the firms that depend on BDA and the second one is the firms that do not depend on BDA, to be able to compare the financial and market performance of the two samples and to ensure that the financial and market performance have been improved only for adopting firms. Research of this nature is important for increasing the use of BDA for making accurate decisions and improving firm performance. It is also important for providing a further understanding of analyzing big data and generating valuable information that can help firms acquire new customers, establish competitive advantages, and improve business value.

It is important to recognize that this study has some limitations and its focus (sample size, and applied methodology), which is an area for future research. Therefore, limitations and future research are discussed below. This study focused on the impact of the BDA on firm performance and strategic decision quality, which limits studying the impact of the BDA on other factors. Future research should examine the impact of BDA on other factors rather than strategic decision quality and firm performance, such as user and customer satisfaction.

Moreover, this study has limitations because of the narrow focus of the financial sectors, especially banks. Thus, the information technology, energy and resources, health care, and chemical sectors are outside the scope of the research. Future research should examine whether BDA has a similar effect on the performance of insurance, health care, and chemical firms. Additionally, this study is limited to studying the factors affecting the adoption of BDA, its critical success factors, and the benefits of adopting new technology. Thus, future research should study the factors affecting the adoption of BDA. Other research is needed to determine the critical success factors of the adoption of BDA and its benefits. Moreover, this study is limited to determining a cost-benefit analysis of adopting new technology. Future research should conduct a cost-benefit analysis of adopting new technology, and a comparison between the users' expected benefits of adopting BDA and its actual benefits.

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ملخص البحث:

أدت التطورات في الحوسبة السحابية، وأنترنت الاشياء، ووسائل التواصل الاجتماعي إلى زيادة حجم البيانات والتي لا يمكن تخزينها أو تحليلها باستخدامأساليب تحليل البيانات الضخمة التقليدية. لذلك أصبحت تحليلات البيانات الضخمة اداءة اساسية للتعامل مع البيانات الضخمة. ويتناول هذا البحث دراسة العلاقة بين تحليلات البيانات الضخمة وكلا من الأداء المالي والأداء السوقي، والتأثير الوسيط لجودة القرارات الاستراتيجية على هذه العلاقة. واعتمدت الدراسة على 150 مشاهدة للبنوك المصرية التي تعتمد على تحليلات البيانات الضخمة والتي لا تعتمد عليها. وتوصلت إلى وجود تحسن في كلا من جودة القرارات الاستراتيجية، والأداء المالي، والأداء السوقي نتيجة الاعتماد على تحليلات البيانات الضخمة. كما توصلت الدراسة ايضا إلى أن التحسن في الأداء المالي والأداء السوقي كان أكبر في الفترة بعد تبنى تحليلات البيانات الضخمة مقارنة بفترة ما قبل التبني. واشارت النتائج أيضا إلى أن التحسن في الأداء المالي والأداء السوقي كان أكبر بالنسبة للبنوك التي تعتمد على تحليلات البيانات الضخمة مقارنة بالأداء المالي والأداء السوقي للبنوك التي لا تعتمد على تحليلات البيانات الضخمة. وأخيرا، أشارت النتائج إلى وجود تأثير وسيط لجودة القرارات الاستراتيجية على العلاقة بين تحليلات البيانات الضخمة واداء الشركة.

الكلمات المفتاحية: البيانات الضخمة، تحليلات البيانات الضخمة، الأداء المالي، الأداء السوقي، جودة القرارات الاستراتيجية.