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The Nexus of Big Data and Big Data Analytics for Managerial Business-Driven Decision-Making: A Systematic Review Analysis

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Abstract

Academics and professionals are expanding their analysis of the implications of big data (BD) and big data analytics (BDA) in business-driven decision-making processes due to the increasing use of these tools in the field. Until now, the impact of BD and BDA on the efficacy of commercial decision-making systems has not been taken into consideration by academics or business executives, who have focused only on the technical aspects of these processes. The purpose of this paper is to review the literature on the relationship between the effectiveness of commercial and industrial decision-making systems and the application of BD and BDA. The study provides crucial information to evaluate whether BD and BDA encourage the use of advanced business intelligence and well-informed decision-making models. In this sense, the study identifies fundamental issues, such as accuracy and efficiency, which support business-driven decision-making processes. In essence, the current work adds theoretical knowledge and practices on BD and BDA for managerial business-driven decision-making and offers a glimpse into potential future agenda avenues to advance understanding in this field.

1. Introduction

Big Data (BD) is a popular concern in today's commercial sector [1]. Businesses worldwide have collected and archived a massive amount of data over the last few decades. For management business-driven decision-making, accessing and evaluating this data is becoming increasingly important [1, 2]. Big or complex datasets that are unsuitable for traditional data processing software are called "BD." We used many methodologies, including predictive analytics, to understand and explain how to extract value from data. To study BD in-depth, businesses require a large amount of raw storage and processing resources, as well as outstanding analytics skills and capabilities. The global BD market was expected to produce 33.5 billion dollars in sales in 2017 and to more than double in size over the next four years [3]. BD refers to the massive amount of data that cannot be processed successfully using existing standard applications [3, 4]. BD processing begins with raw data that has not been aggregated and is frequently impractical to keep in the memory of a single machine. BD is a jargon that refers to massive amounts of data, both unstructured and organized, that inundates businesses daily. Insights from BD analysis can be used to make more informed choices and calculated business moves [3, 4]. Gartner defined BD as " high-volume, high velocity, and/or high variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation [5]."

The increasing interest in the application of BD in the business world has prompted academics and professionals to delve deeper into the changes brought about by the use of new technologies in corporate decision-making processes [5]. Researchers and managers have, until now, only addressed the technical aspects of BD, failing to emphasize the influence these traits have on the effectiveness of decision-making systems [6]. The creation of BD is outpacing the advancement of computers and storage technologies. According to a report by International Data Corporation (IDC), by 2020, there will be enough data to fill a stack of tablets that is equivalent to 6.6 times the distance between Earth and the Moon. According to analysts, the amount of unstructured data that needs to be managed is increasing, going from 31% in 2015 to 45% in 2016. BD is a massive volume of organized and unstructured data that is difficult to manage with traditional database and software processing techniques. Among the difficulties include information analysis, capture, curation, search, sharing, storage, transportation, and visualization [7]. However, BDA looks through this massive volume of data (BD) to find unnoticed correlations, trends, and other insights. With the technologies of today, data analysis can yield results nearly instantaneously. Using more conventional business information technologies, this approach is less effective and takes longer [7]. BDA assists organizations in gaining a deeper understanding of the information in their data and determining which data is most crucial to their operations and future choices. BD analysts are usually looking for knowledge derived from data analysis [2]. However, there are drawbacks as well as advantages to the subject of big data analytics (BDA). The following are some of the benefits of BDA [8]: lower costs, quicker, more accurate decision-making, and new goods and services.

Researchers, practitioners, and industry experts have increased the amount of time they spend studying how the use of new technology has changed society. As a result of the increased interest in the implementation of BD and its analytics in the management sector, these technologies include industry 4.0 technologies in business [8]. Until now, academics, practitioners, and managerial staff have ignored the influence that these elements have on how well firms make decisions in favor of concentrating solely on the technical aspects of BD and BDA. To effectively manage business operations and steer the business sector in a market that is growing more dynamic and competitive, managerial employees must possess the ability to make strategic decisions.

Considering the significant degree of uncertainty and risk associated with managerial business choices, the collection, evaluation, and analysis of reliable data and information play a fundamental part in this process [9]. In an unpredictable world, organizations need to integrate their knowledge resources with their strategic dimension [9]. BDA is crucial because it enables businesses to use enormous volumes of data in a variety of forms from a variety of sources to discover possibilities and hazards. This facilitates speedy decision-making and increases an organization's profitability in the field of management business-driven decision-making. The new lubricants for any company looking to make strategic managerial decisions that are motivated by business are BD and BDA [10].

1.1 Contribution of the Paper

Organizing the literature on the relationship between BD and BDA in the context of business-driven decision-making is the aim of this study. Additionally, a helpful justification of whether and how BD and BDA are positioned as enablers for the adoption of complex corporate-driven decision-making representations is given. This study looks at potential levers to assist in business decision-making and suggests an agenda for future research. Furthermore, by highlighting potential future avenues for BD and BDA research in these domains, this work adds a theoretical and managerial component to the literature on BD and BDA for corporate-driven decision-making.

The paper is organized as follows: the technique employed and the primary theoretical contributions examined are covered in Section 2. The work's findings and discussions are covered in Section 3, where a conclusion is ultimately reached. The following goal served as the study's guide: *To establish the fundamental facets of the nexus of BD and BDA for the managerial business-driven decision-making process.*

In summary, the current paper provides both theoretical and business-driven-managerial contributions to the literature on BD, BDA, and business-driven decision-making, defining future perspectives to advance the knowledge.

1.2 BDA Trends

By 2018, the rise of visual discovery tools had halted, and product commoditization had set in. By 2020, new cloud pricing models catered to specialized analytics workloads, which contributed to a five-fold rise in cloud versus on-premises analytics spending growth. By 2026, G2000 businesses will have policies in place to prevent unintended consequences of cognitive systems, such as noncompliance and ethical quandaries [2]. The volume of data in the world is growing at a 40% yearly rate. With the advent of the Internet-of-Things (IoT) and other 4.0 industrial innovations, one of the main BDA Trends of 2018 and beyond was the integration of multiple new sources of BD and its analytical technologies into the Data Management environment. For the IoT, laptops, cellphones, and machine sensors generate enormous amounts of data (Table 1).

Furthermore, new units of measurement have emerged as a result of the availability of data. Exabytes, Pet bytes, and Zettabytes are the current numbers used to indicate data capabilities; further units will be added later. The amount of data contained in a single file or file system can be measured in terms of bytes. However, data sizes might increase dramatically when working with BD volumes. Table 2 examines multiple research publications and their predictions about future BDA trends. In contrast, Tables 1 and Figure 1 show the trend of data volume measurement units and data volumes projected, respectively. By 2025, the globe will produce 463 exabytes of data per day, or 463 billion gigabytes [12]. The amount of data has two effects: 1) Its worth and capacity for comprehension; and 2) Whether or not it satisfies the prerequisites for BD.

Table 1. Examples of data volumes trends. **Source:** Synthesized by the Author

Unit	Value
Kilobytes (KB)	1,000 Bytes
Megabytes(MB)	1,000 Kilobytes
Gigabytes (GB)	1,000 Megabytes
Terabytes (TB)	1,000 Gigabytes
Petabytes (PB)	1,000 Terabytes
Exabytes (EB)	1,000 Petabytes
Zettabytes(ZB)	1,000 Exabytes
Yottabytes(YB)	1,000 Zettabytes

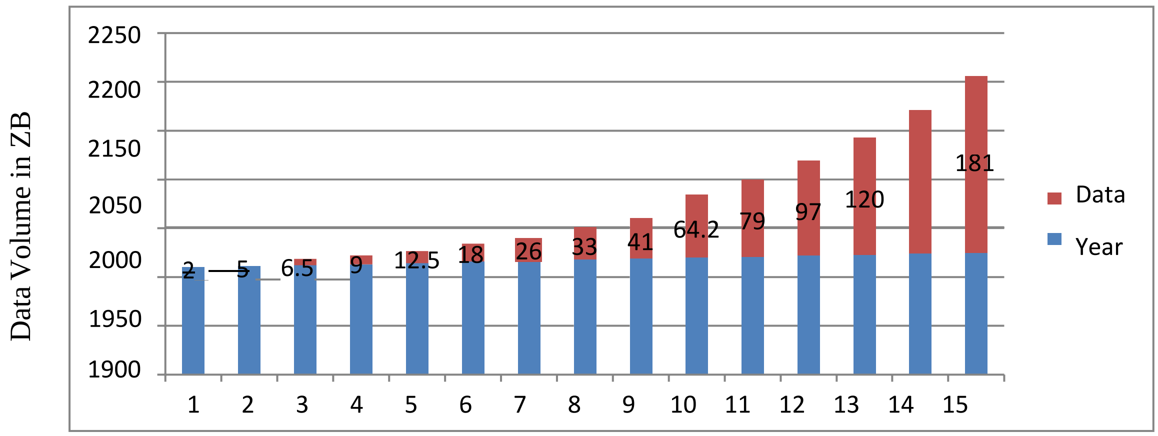

Figure 1. Data volumes forecast in zettabytes. Adapted from Holst [12]

Table 2. Some research papers and theirpredictions on BDA future trends. Source: Synthesized by the Author

No.	Description
001	Improved BDA integration might result in annual savings for healthcare of up to $399 billion, according to recent studies. This translates into a yearly cost savings of $1,000 for each individual with facility access.
002	The White House has poured an astounding $200 million into BDA implementation programs.
003	A 10% improvement in data accessibility can result in a net income boost of more than $65 million for a typical Fortune 1000 company.
004	If retailers choose to completely employ BDA, they can maximize their operating margins by approximately 60%.
005	Of the 85% of companies that have attempted to become data-driven, only 37% have been successful in their initiatives. The reason for this is the executives' ambiguity. In due course, the remaining companies will also advance to the same stage.
006	Currently, only 0.5 percent of the data that is available is being analyzed and used. Think about the options available to you here.

Businesses are increasingly transforming their data into insightful business information, suggesting a substantial opportunity to gain a competitive advantage. As BD expands, businesses will need to learn how to handle their data efficiently within the framework of management decision-making. Combining business intelligence capabilities is essential to remaining ruthless, and BDA is the best platform to deliver essential up-to-date data [2]. In 2017, a few businesses increased the usage of their services and tools, which turned BD into graphs and visualizations. As a result, customers had a better experience since researchers were able to gather and organize public data more efficiently. It also makes business decision-making for managers more effective. Those in the business intelligence field projected that data discovery and visualization would become important trends. Through data discovery, data presentation has evolved to provide deeper business insights. Thus, the use of visualization models to transform data into useful insights is becoming more and more common. Because visual patterns are simpler to identify and understand and because visual patterns are processed by our brains more quickly than other types of patterns, humans prefer visual patterns [13, 14]. Using the subconscious, this exercise helps decision-makers quickly examine and analyze information. The brain's capacity for pattern recognition is stimulated by persuasive images, and useful visualization models will be the most effective option when working with larger data sets. One of the main BDA Trends for 2018 is [14].

Companies that haven't yet adopted Hadoop just over 50% of them did so in 2017, per a Gartner survey will consider doing so. However, rather than being on-premise, this will probably be on a cloud vendor of choice [15]. On-premise installations are typically the best choice for big cluster sizes. 2018 cloud-based Hadoop deployments will be primarily motivated by two objectives: complexity management and cost reduction. Additionally, algorithmic markets will exist. Forrester predicts that businesses will soon realize they can purchase algorithms instead of having to program them and contribute their data. Existing services like Data Xu, Kaggle, and Algorithmic are expected to continue growing [15]. According to Gartner, autonomous agents and things, such as intelligent advisers, virtual personal assistants, self-driving cars, and robotics, will also continue to be a significant trend in this nexus. Machine learning is ranked as the top strategic trend for 2018 by Gartner. Furthermore, Ovum predicts that machine learning will play a major role in data preparation and predictive analysis for organizations in the future. With a projected $430 billion in benefits, companies using data will surpass their non-using counterparts in terms of productivity by 2020 [2, 16]. 2019 will bring additional advancements in business intelligence and artificial intelligence, which will work together even more to achieve higher levels of competence. The existing capacity of machine learning algorithms to identify patterns, habits, and trends may render human decision-makers redundant shortly.

A lot of businesses and business analysts have moved into predictive analytics to accurately forecast future behaviors to increase the effectiveness and profitability of their organizations due to the easy availability of interactive software on the market. In the areas of fraud detection, lowering market risks, maximizing marketing campaigns, and enhancing business operations, predictive analytics is being used extensively. New job roles will also be created; to advance in their careers and businesses, coders must become proficient in business intelligence and familiarize themselves with all aspects ofdata. There will be a shortage in the US in 2018 of roughly 190,000 data scientists and 1.5 million managers and analysts who can comprehend and use BDA for decision-making, according to a McKinsey GlobalInstitute study.

According to a Glassdoor report, the average pay for a data scientist is $116,000 [17]. BD Scientists make an average salary of US$123,000, Lead Data Scientists make US$108,000, and Data Scientists and Principal Data Scientists make US$133,333 [18]. Additionally, studies showed that by 2020, the Indian market would be worth $8 billion, creating a demand for over 50,000 highly qualified data scientists and BD specialists. This also takes place. Data scientists, data engineers, data architects, data administrators, data analysts, business analysts, data or analytics managers, and business intelligence managers are among the career options available to those with training and experience in data science. IDC predicts that the scarcity of personnel with expertise in data management and architecture will join the ranks of analysts and scientists in the field of BDA. Ultimately, the business community now has a solution thanks to access to BD and knowledge of how to use it to precisely forecast customer needs. A variety of formats, including text, image, and video, could be used to make data accessible. BDA is expected to be the most potent technology of the future, providing answers to a plethora of consumer-focused queries that businesses are currently attempting to address [19].

The following areas are predicted to show positive correlations for the BDA in the future: a) The increasing velocity of BDA (real-time data/insights and real-time, automated decision making); b) The heightened veracity of BDA (data quality, data observability, and data governance); c) Platforms for storage and analytics are handling larger volumes of data; d) Processing a greater variety of data is easier; e) Democratization and decentralization of data (no-code solutions, Micro services/data marketplaces, and Data mesh); and f) be prepared for the future of BDA [20]–[22]. Despite what the paragraph before it emphasizes. It's hard to predict the future because anything can happen, but there is a race to mimic human intelligence, spearheaded by well-known corporations like Microsoft, IBM, Google, Facebook, Amazon, and Baidu. These companies have substantial financial resources and are heavily investing in BD, so it seems certain that "BDA" will become a reality very soon. Future research can build on the findings of this paper by conducting additional research [22]–[24].

1.3 Challenges Related To BDA

Even though BDA has a plethora of potential benefits for business managers making decisions, BDA will confront significant privacy challenges, particularly in light of the new European Union privacy regulation. Businesses will have to confront the BD and its analytics" regarding their policies and procedures for privacy. Data will be a factor in 50% of business ethics violations by 2018 [99]. Improved data governance practices will put businesses in a strong position to handle obstacles with ease and control expenses [2, 25]. The emergence of complex data formats, such as documents, audio, video, social media, and newer smart devices, is another factor contributing to BDA. According to the IDC report, there will be up to 450 billion online business transactions per day for managerial decision-making in the workplace [26]. A study conducted by Cisco predicts that, in just five years, there will be 50 billion connected devices, producing enormous amounts of data. The IDC predicts that by 2020, there will be up to 450 billion daily business transactions (Business to Business and Business to Consumer) conducted online [27]. By 2020, there will be 6.1 billion smartphone users worldwide, surpassing the number of basic fixed phone subscriptions. There will be more than 50 billion smart connected devices in the globe in just five years, all of which will produce data that can be shared, gathered, and examined [28]. Even though BDA has many proven advantages, there are still many issues that need to be resolved before BDA can reach its full potential. A portion of these difficulties stem from the features of BD, while others are caused by the models and analysis techniques in use today and by the constraints of the data processing system as it stands [29].

According to Zicari and Akerkar [30], the broad BDA challenges fall into three primary categories: data, process, and management challenges. These categories are based on the data life cycle. Data challenges pertain to various aspects of the data, such as volume, variety, velocity, veracity, volatility, quality, discovery, and dogmatism [30, 31]. On the other hand, process challenges are associated with various techniques, such as data capture, integration, transformation, model selection for analysis, and result delivery. Issues related to privacy, security, governance, and ethics are examples of management challenges.

Defining and Detecting Anomalies in Human Ecosystems; Distributed Storage; Content Validation; BDA marketplaces; Sentiment analysis (or opinion mining); Text mining; Finding true relationships in the data; and Volatility are additional miscellaneous challenges. Among the difficulties in data analytics [2] are data analysis and storage, Knowledge discovery, complex computations, data visualization and scalability, and information security. When compared to traditional computing models based on total data, the inherent difficulty of BDA (including complex types, complex structures, and complex patterns) makes its awareness, depiction, understanding, and computation far more difficult and leads to sharp increases in Computational Complexity [32]. To study data-centric computing paradigms based on the characteristics of BD, we will need to concentrate on the entire life cycle of BDA applications to address the computational complexity of BDA applications [33, 34]. However, when it comes to managing computational complexity, uncertainty, and inconsistencies, current BDA tools tend to perform poorly [34, 35]. The development of methods and tools that can effectively handle computational complexity, uncertainty, and inconsistencies presents a significant challenge. One of the main problems in BDA is knowledge representation and discovery. It encompasses several subfields, including information retrieval, representation, archiving, management, and authentication [36, 37]. In terms of BDA, incremental techniques have good scalability properties. A naturally dramatic shift in processor technology is occurring as the number of cores increases, as the data size is scaling much faster than CPU speeds [36, 37].

People's minds are the source of knowledge, and if it is used wisely, they can aid businesses in adding value. The general definition of knowledge management is a systematic method for producing, disseminating, and applying knowledge. Knowledge management in this context is Information and Communication Technology (ICT) systems created to support and facilitate the production, diffusion, and application of knowledge in businesses [35]. ICT serves as an enabler for knowledge management developments and is involved with the social and cultural aspects of the organization [38, 39]. Systems for managing knowledge are therefore used to identify, distribute, and utilize knowledge as well as to incorporate it into the processes of identifying and solving problems. It is essential to create and use fresh data mining techniques or take advantage of artificial intelligence to extract information from large data utilizing BDA technologies that can add value for a company [36]. Other researchers [38] have stressed the significance of IT and, in particular, of BDA in encouraging the pursuit of a range of goals in diverse industries, which is consistent with these ideas.

For instance, Nguyen et al [38] identified and tracked food fraud and food safety issues using the Rapid Alert System for Food and Feed (RASFF) database. Scientific databases are another source of textual information that can be used to identify risks to food safety among others [40, 41]. A low-cost sensor and actuator network platform can be created using modern ICT [42, 43]. With the use of this platform, production efficiency may be increased while also improving quality, reducing environmental damage, and using fewer resources like water and energy. Other researchers have surveyed the use of BDA in the agriculture industry [44, 45]. They emphasized the use of BDA to give farmers real-time predictive information about company operations and operational business-driven decisions. The current state of machine learning techniques in agriculture was examined by Infante and Mardikaningsih [46], and Szymkowiak et al. [47] who made the case that real-time artificial intelligence enables computer programs to offer recommendations and insights that might aid farmers' decision-making processes. A lot of firms still deal with daily instances of bad data quality. One factor that contributes to this poor data quality is presumed to be a lack of awareness of the connections between BD, BDA, and strategic business decision-making. Studies to date [48-51] have primarily concentrated on the characteristics and potential of IT, without adequately highlighting the effective contribution that these tools are capable of ensuring to the decision-making dynamics of organizations. The analysis of the relationship between BDA and decision-making has not received the right attention upto this point, leaving open the subject of the actual levers that may be activated for the betterment of business decision-making processes.

2. Methodology

A systematic review analysis was carried out, utilizing Preferred Reporting Items for the Systematic Review and Meta-Analysis (PRISMA), taking into account the information provided by Zhou et al. [52]. To understand the scholarly aspects surrounding the intersection of BD and BDA for business decision-making, this study makes use of the existing relevant literature from various scholarly databases, including IEEE, Wiley Online Library, ACM Digital Library, Taylor and Francis, Scopus, and Science Direct. To find the most pertinent publications for the study, regardless of where they were published, the articles were read using specified inclusion and exclusion criteria (Table 3). Because it allows for a thorough screening of pertinent current literature based on the pre-determined group of circumstances, a Systematic Review Analysis (SRA) was selected as the best methodology to meet the study's objectives. Additionally, because it is carried out under the guidance of a step-by-step systematic approach, the methodology is known to produce an original piece of work [5]. Such systematic reviews are conducted in a method that allows for replication, resulting in the production of the same findings from identical data. This suggests that the literature used is specifically relevant to the subject being studied. The search for papers was completed in the various reliable databases specified in the first paragraph of this section to perform the broadest review of the literature as possible and to consist of as much feasible research related to the issue. Preferred reporting items for the systematic review and meta-analysis (PRISMA) (Figure 2) statement were used in conjunction with SRA to increase the depth and reliability of the review results (Sarkis-Onofre et al., 2021). In addition, PRISMA serves as a manual for writers, reviewers, and editors [53]. Four (4) phases were taken in the review under the PRISMA claim [50].

Step 1: Identifying Articles for Review: This step involved running the searches designed through the abstract and citation databases selected. Here, the research questions were framed, with the relevant literature subsequently identified. This involved defining keywords and databases with logical justifications. Keywords like BD and BDA; the nexus among BD and BDA for Business decision-making, and Business decision-making using data were identified. The keywords/combination of keywords and chosen databases were determined through the conduction of brainstorming sessions and discussions between authors and further the findings were relayed before the experts to have final results of which databases to consider as well as which keywords/combination of keywords that should be considered for the search. The keywords were taken in combination as a way to keep the scope of the study

Step 2: Screening the Articles: The reading of the title and abstract of each record happened under this step. This step is intended to determine whether the article contains content that would be relevant to the study. The inclusion and exclusion criteria were established, according to which the references retrieved from online and manual searches were scanned and the relevant articles were marked.

Step 3: Eligibility: This involved taking the articles that remained after the title and abstract screening. The intention was to determine whether these articles would help to address the study goal. The quality of the literature retrieved was assessed and its relevance to the study was evaluated.

Step 4: Inclusion: After excluding irrelevant publications, the number of studies to be included in the review for content analysis was determined. Ninety-two (92) articles were removed based on defined exclusion criteria as shown in Figure 1 below and seven (7) articles were removed at the eligibility level. According to the publication information of the remaining 51 articles nominated; 45 articles came from journals and six came from other sources. Even though the inclusion and exclusion conditions were strictly adhered to, certain additional references that were mentioned in the chosen articles were added throughout the review process.

2.1 Some Common Attributes of the Selected Publications

2.1.1 The Exclusion and Inclusion Criteria

Numerous inclusion and exclusion criteria have been used because the paper selection procedure is important for adding scientific value to the systematic literature review. Therefore, we decided to concentrate on research on BD and BDA for business-driven decision-making. The modified inclusion and exclusion criteria are displayed in Table 3. Papers that were not published in English or ones that were still in publication at the time of selection were disqualified. The goal of our work is to examine the relationship between BD and BDA for managerial business-driven decision-making; hence, we have also incorporated quantitative, qualitative, and case study analyses. Additionally, a variety of epistemological stances have been adopted to emphasize the topic's multidisciplinary aspect.

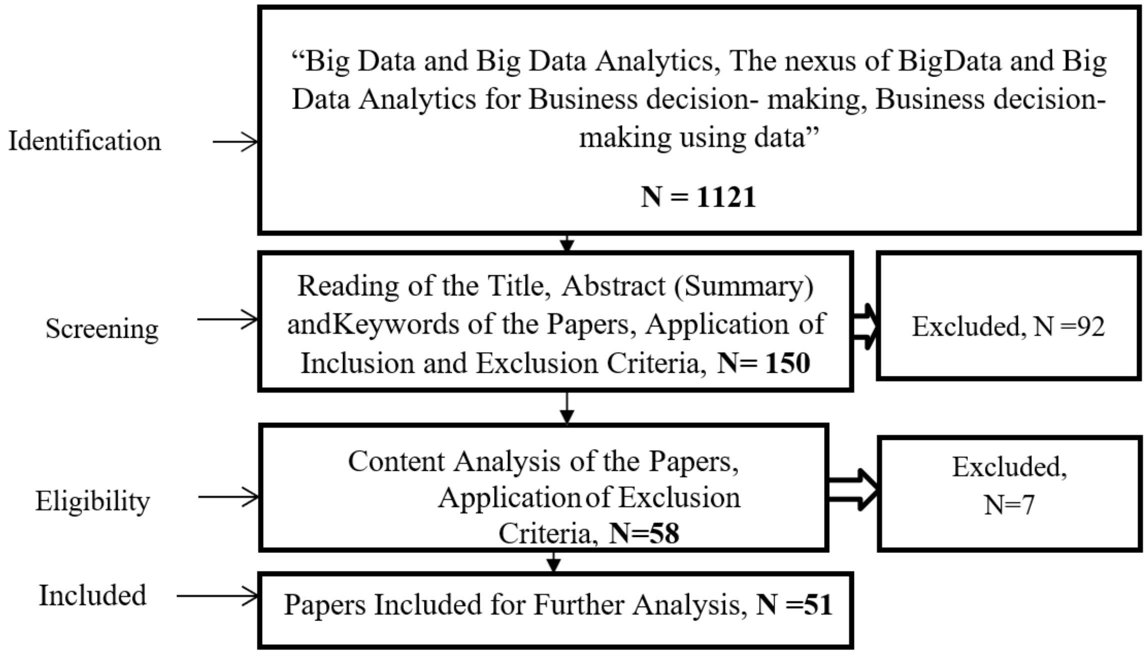

Figure 2. Process flow of PRISMA assertion.

Table 3. Inclusion and exclusion criteria of publications

Inclusion criteria	Exclusion criteria
Books, Empirical studies, Editorials, Fields of social science, Information science, Economic science, Humanities, English language articles, Articles in academic journals, Case studies, quantitative and qualitative analyses, and epistemological approaches	Summaries of Conferences, Convention lawsuits, Book reviews, Field of agriculture science, Interviews, Technical as well as health science, Summaries of meetings, Editorial letters; Non-academic texts, and non-English papers, Papers that were still in publication

2.1.2 Distribution of Articles by Publication Year

Only publications released between 2014 and 2023 were chosen. To benefit from a period in which the associated theme, in addition to a commercial dynamic, has found considerable resonance, scholarly articles on the topic should be as current as feasible. The systematic literature review concentrated on reports written for both business leaders and a larger audience, as well as on research papers published in both national and international scientific journals. 8 papers were published in 2023; the years with the fewest publications were 2014, 2015, and 2016. Indicating the present interest in this area of study, the majority of the papers were published between 2018 and 2023 (Figure 3).

2.1.3 Distribution of articles by database

Figure 4 displays the distribution of the selected articles by database source. The IEEE database contained 11 papers, then 7 papers from Wiley Online Library, 7 papers from the ACM Digital Library, 5 papers from Taylor and Francis, 5 records from Scopus, and 4 records from Science Direct.

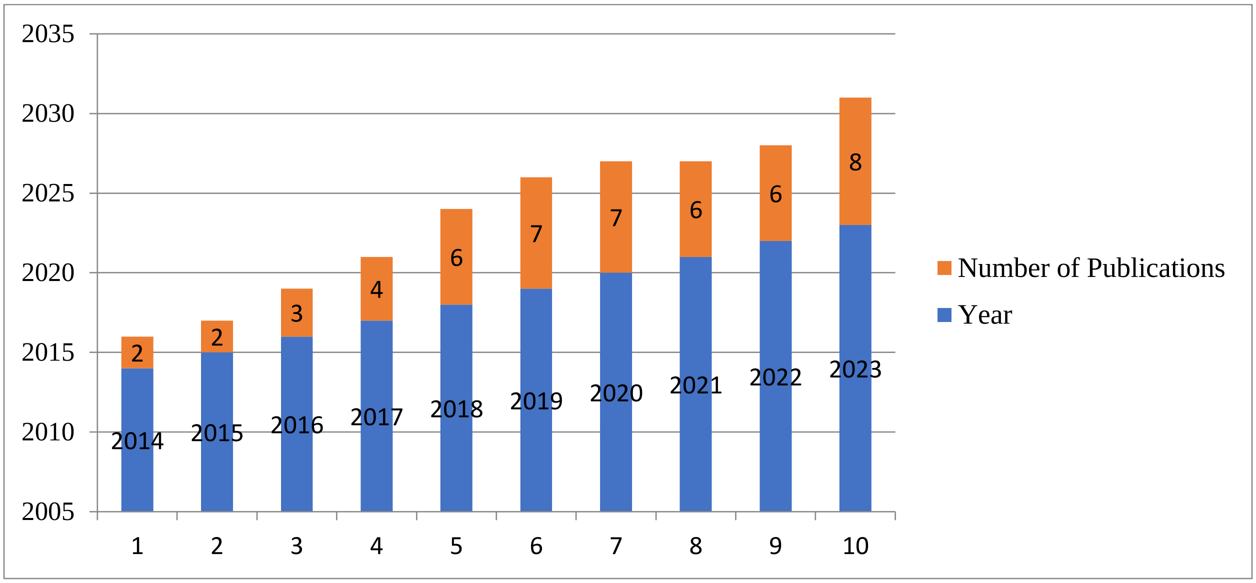

Figure 3. Distribution of articles by publication year.

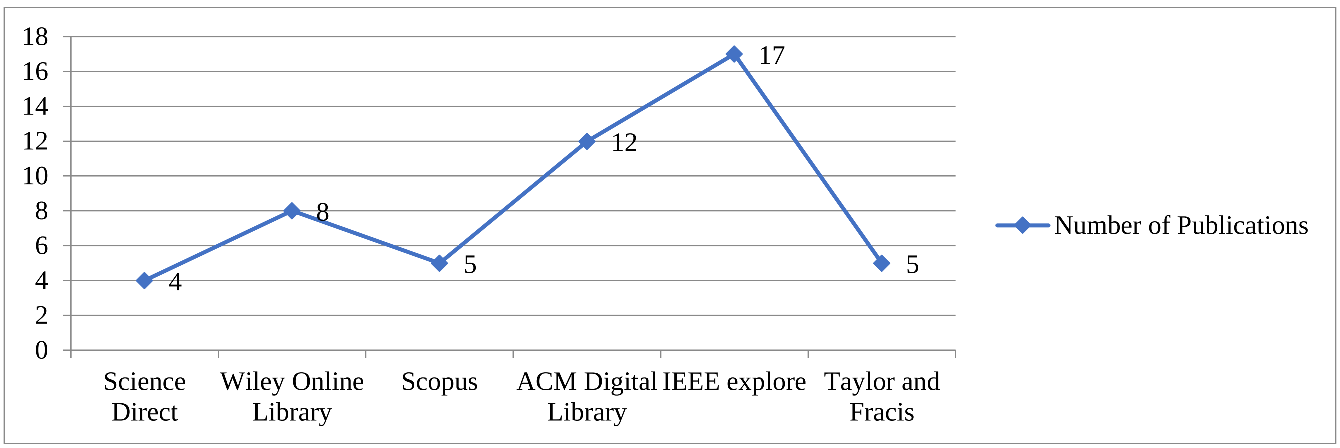

Figure 4. Distribution of articles by database.

2.1.4 Publications Covered for Assessment

Table 2 summarizes some of the publications considered for content analysis of the study. The papers focused on various dimensions of BD and BDA for management and related functionalities adoption across various settings. The summary (Table 4) gives important information about the publications that is to say: the author (s and construct (s) covered.

Table 4. Some of the discovered papers and their construct.

Reference	Construct
[55]	COVID-19: challenges to GIS with BDA
[56]	Uncertainty in big data analytics: survey, opportunities, and challenges
[57]	Information and Reformation in Knowledge Management Systems
[58]	A new model for integrating BD into phases of the decision-making process
[59]	Self-service analytics for data-driven decision-making during the COVID-19 pandemic
[60]	Emerging Data Sources in Decision-making and AI
[61]	Data Value, BDA, and Decision-Making
[62]	Self-Building Artificial Intelligence and Machine Learning to Empower BDA
[63]	Decision-making Technology Based on BD
[64]	Influence of artificial intelligence (AI) and BDA on organizations performance
[65]	Artificial intelligence and machine learning as business tools
[66]	Pattern detection model using a deep learning algorithm for power data analysis
[67]	A comprehensive review of BDA throughout the product lifecycle to support sustainable smart manufacturing
[68]	Circular economy and BDA
[69]	Creating strategic business value from BDA
[70]	Sustainable business model innovation with BD
[71]	BD and sentiment analysis to highlight decision behaviors
[72]	Towards felicitous decision making: An overview on challenges and trends of Big Data
[73]	Decision support systems for agriculture
[74]	Marketing ecosystem using BD era
[75]	Smart recovery decision-making for end-of-life products in the context of ubiquitous information and computational intelligence
[76]	The BDA regime shift in real estate
[77]	Multi-level governance for sustainable innovation in smart communities
[78]	Advanced Data Collection and Analysis in Data-Driven Manufacturing Processes
[79]	Decision-Making Based on BDA for People Management
[80]	Data-driven sustainable intelligent manufacturing based on demand response for energy-intensive industries
[81]	Internet of Things (IoT) and BDA for digital manufacturing
[82]	A review of industrial BD for decision-making in intelligent manufacturing
[83]	Leveraging BDA in Healthcare Enhancement
[84]	Technical considerations when implementing digital infrastructure for social policy
[85]	Utilization of text mining as a BDA tool for food science
[86]	Factors influencing BD decision-making quality
[20]	Optimization and decision-making with BD
[88]	The importance of BDA in business
[89]	BDA, and artificial intelligence in accounting

[90]	BD-assisted social media analytics for business models for business decision-making system competitive analysis
[91]	Measuring customer value co-creation behavior with BD
[92]	Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine
[93]	Market acceptability assessment using BDA and analysis-evidential reasoning
[94]	BDA capabilities
[95]	Modeling of Business Intelligence Systems
[96]	Without data, you're just another person with an opinion
[97]	The nexus between BD and sustainability
[98]	The Empirical Nexus Between Data-driven Decision-Making and Productivity
[99]	Big data analysis for decision-making processes: challenges and opportunities for the management of healthcare organizations
[100]	Big data challenges: prioritizing by decision-making process using analytic network process technique, Multimedia Tools, and Applications
[101]	Introduction to the Handbook on the Politics and Governance of Big Data and Artificial Intelligence,
[102]	Issues with big data,
[103]	The nexus between data analytics and firm performance

3. Results and Discussion

The research demonstrates the increased interest of academics and professionals in all the elements considered essential to the administration of enterprises and organizations for BD and BDA. In this context, Figure 3 demonstrates the exponential growth in recent years of scientific contributions targeted at studying the impact of technology, particularly BD and BDA, on the effectiveness of business-driven decision-making processes. The pattern that was revealed in Figure 3 cannot be taken as reality. The overall number of worldwide scientific publications, which has risen over time, should be properly being compared to the facts presented. The paper emphasizes the widely acknowledged significance of BD and BDA as well as how important it is to use these tools to assess the efficiency of business-driven decision-making processes. The comparison between the data in Table 4 and the total number of all scientific contributions published in the various nations provides persuasive evidence that the findings produced by the geographical distribution of the 51 selected publications are significant.

According to the industries to which they belong, several theoretical methods can be used to study the relationship between BD and BDA for business-driven decision-making, according to the examination of the contents of the 51 selected publications. BD has been cited as having a significant influence on both the public and private sectors, working as a catalyst for business-driven decision-making procedures [70, 71]. The majority of the chosen studies concur with the notion that creating and implementing cutting-edge analytics tools can facilitate the usage of information required for business-driven decision-making [76, 81, 96]. Scholars have increasingly focused their attention on finding potential economic and technological levers that can enhance the business-driven decision-making processes of companies to move toward more flexible and effective business-driven decision-making models. Accordingly, the primary goal of technical advancements, as well as the usage of BD and BDA, is to offer relevant information to direct decision-making processes in an efficient and long-lasting manner [63]. Additionally, according to other academics, for technologies to be effective, particularly concerning corporate information systems, they must be in line with the goals pursued by businesses, effectively manageable and controllable by managers, and able to deliver timely, accurate, and cost-effective information [10]. If properly applied, BD and BDA techniques can significantly improve organizational learning, impact, and ultimately the efficacy of decision-making systems [5]. Based on previous research, the work specifically presents the levers on which BD and BDA act, allowing for more effective governance of business-driven decision-making processes [58, 76]. In other words, the work identifies the regrouping of the fundamental characteristics of BD and BDA, as well as synthesizes the variables reflecting structural prerequisites for each of them. These can boost organizational learning and the effectiveness of business-driven decision-making procedures.

Through a systematic review of the literature on the potential intersection of BDA and business, key elements that can enhance business processes have been discovered. These elements include the following: 1) correctness, defined as a tendency to provide high-quality goods and services in an objectively short period. In particular, timeliness relates to the capacity to meet all conceivable interlocutor needs by promptly attending to outside requests [71, 92]. Business managers can pursue significant results in terms of services provided, users served, user response times, frequency of services provided, and, most importantly, in terms of quality of services provided, such as physical and cultural accessibility, timeliness, courtesy of operators, and facility condition; 2) efficiency, defined as the capacity of BD and BDA to enable an evolution in perspective in business [70, 74, 93]. It has been suggested that this shift has occurred from top management's intuition to a culture of business-driven decision-making supported by data, marking a significant turning point in managerial culture management. In keeping with this development, various researchers [5, 56, 70, 76, 81, 85, 99] have published their findings. The aforementioned points are consistent with the arguments made by other academics [10, 58] who highlight how the development of BD has given rise to a concept in which top management's knowledge and skill in making accurate predictions about industry developments will be the primary factors in decision-making. These analyses are performed by analysts and subject matter specialists, who explain why there, will likely be a significant growth in the need for statisticians and data analysts in businesses; 3) precision is the capacity to innovate through the appropriate use of data. In actuality, innovation and technology are intertwined in terms of both technical advancement and the market economy. The crucial aspect of competitiveness in obtaining added value is sensitivity and precision to innovation, but it is not just restricted to the technological field; it exists in every sector. This is because innovation increases demand for commodities that can spur economic growth in a market economy [80, 99]. Innovation acts as a driving force behind consumption. The accuracy ensured by BD and BDA utilization encourages productivity growth, boosting the effectiveness of data collecting, optimizing expenses, and lowering the likelihood of making potential errors. Furthermore, the proper application of BD and BDA is the only way to ensure the most efficient approach to handling the company's BD [78]. This makes it possible to directly support business managers, quickly identifying any process flaws or failures, and planning interventions with great ease and precision. Additionally, by involving all parties involved in the business processes in various positions, it is feasible to ensure the processes' transparency.

4. Future Research Directions/Agenda

The assertions in this paper are supported only theoretically, thus more research may be necessary to fully understand any potential practical difficulties. A lack of specific AI operations that could not be accessed was another reason why our study's assessment of the BD and its analytics for business managerial decision-making cannot be viewed as definitive given the novelty of the topic and the need to draw from multiple fields of research. Academic papers frequently omit details about the workings of AI because these functionalities are largely proprietary. Secondly, some studies on BD and BDA in healthcare decision making such as gray literature and reports that were not published in the databases that were reviewed, were left out even with a comprehensive search strategy in place. In addition, there are still several industries where the BD and its analytics are not being applied. Furthermore, there is still a dearth of scholarly research that goes beyond technological and managerial perspectives. Regarding this, while some advances in the domains of engineering, geography, and mathematics have been made public, the subject has not yet been explored by other study streams. These would include environmental sciences, biology, physics, and healthcare. In addition, social sciences, sociology, ethics, political science, education sciences, and economics ought to tackle the sustainable growth of BDA.

The study aimed to review only academic publications from six scholarly databases, excluding publications from a forward and backward search, white papers, magazine articles, and other scholarly literature databases, all of which would have helped capture more issues regarding BD and BDA for managerial decision-making. Only the article title was used as a search criterion; yet, using the abstract as a filter might have shown more insightful articles. There were only a few search terms available because several publications covered BD and BDA for decision-making with terms that might not have come up in this review's search results. Additionally, the majority of our sample came from scholarly journals. Since BD and BDA for management business-driven decision-making are primarily pushed by the industry, this phenomenon may also be covered in several high-caliber professional papers. This could make it more difficult for this article to give a thorough overview of the most recent advancements in this field. Each of the featured publications is a peer-reviewed journal article. Consequently, the topic distribution of research about BD and BDA for management business-driven decision-making may not be reflected in the classification scheme. This Systematic literature review (SLR) restricts its search to book chapters, conferences, and journals only. Thus, a small number of dissertations as well as other electronic media sources, including periodicals and newspapers, may be taken into consideration for upcoming work. The authors did, however, run into some difficulties in getting information out of some of the publications, while making every attempt to obtain all pertinent materials that are necessary concerning the study topic and purpose. For instance, the authors eliminated certain articles with irrelevant information.

In addition, future studies should take into account the issues raised by Alharbi and Alnoor [9] regarding the application of BD and its analytics to new sectors and areas where this literature has not yet been developed, the trends in BD and its analytics in traditional research fields, and the consideration of BD and its analytics when analyzing current issues. In this way, the results about the most significant and frequently cited authors, sources, and papers, along with the compilation of the most commonly used keywords, can assist academics in determining the most pertinent research questions and the hottest subjects that pique interest in the field right now. Both academic studies and practical applications should take into consideration the link between business and technological developments and managerial business-driven decision-making. Therefore, future studies and real-world implementations should be aware of the development of Web 3.0, or Semantic Web, and the conceptual models mentioned by Yu and Chen [19] for business-driven decision-making, where AI and the IoT ubiquitous and pervasive web are key components. Furthermore, it is imperative to closely monitor the evolution of BDA itself, encompassing not only the numerical and alphabetical data sourced from internal warehouses of organizations, but also the management and mining of data from social networks, external websites, smartphones, and increasingly decentralized cloud-based data associated with images, tastes, and other senses.

Future investigations should get around this study's shortcomings. More research can employ novel techniques, include qualitative data, or take a more targeted approach to business development and analytics. Adding a larger sample from other databases to the study, taking into account different document types like conference proceedings, professional papers, and documents published in other languages, or concentrating on a particular region would all be beneficial research directions. Future research endeavors may also expand upon the principal themes delineated by this study, enhance and supplement the analyses carried out, and introduce novel approaches that offer pertinent methodological advancements in BD and BDA for managerial business-driven decision-making. Modern applications operate on enormous volumes of data, which presents interesting challenges for parallel and distributed computing platforms. These challenges include developing storage systems large enough to hold these massive datasets, gathering data from widely dispersed geographical sources, putting data into storage systems, and performing a wide range of computations on data. These systems will need to change in the future to take advantage of application-specific optimizations for managerial business data-driven decision-making as data sizes increase and application domains diverge. Future systems may transfer part of the computation to the data sources themselves to address the highly distributed nature of data sources and save costly data movement expenses. Realizing the distributed software platforms required for BDA has been made possible in large part by recent hardware advancements.

Software innovations will continue to be driven by future hardware innovations, such as advancements in processor technology, memory/storage/hierarchies, and network architecture (software-defined networks). Reducing the amount of time needed to move data between storage and compute nodes in a distributed environment, or from storage to the processor, will be a major design priority for these systems.

5. Conclusion

This paper has examined the current state of the art as well as emerging trends in the analytics literature related to BD and BDA concerning the nexus of making business managerial decision making. The findings demonstrate the existence of numerous theoretical research fields that have taken a diverse approach to the subject. This study's goal was to look into the relevant scholarly works by academics to analyze the nexus of BD and its analytics for business-driven managerial decision-making. It has been feasible to organize the research on a subject that continues to draw special attention because it influences business behavior and, consequently, performance, through the use of a systematic literature review. Empirical results of the study include the possibility of developing new business models based on BD and BDA for better managerial decision-making for businesses, as well as novel approaches to operations management and internal and external organization's logistics chains. The purpose of the paper can be to have a better practical and operational understanding of the phenomenon that has been noticed. In addition, in light of what has been discussed, the paper can be seen as a helpful tool for business managers and executive staff as well as scholars, with a focus on the recognition of the benefits resulting from the management of business-driven decision-making processes. Other strengths of the study are being specific and reproducible which can be weaknesses on the other hand. For example, researchers only answered specific research questions of high importance like "To establish the fundamental facets of the nexus of BD and BDA for a business-driven decision-making process". Regarding the article's theoretical significance, the analysis that was done creates and sheds light on new opportunities for BD and BDA in making managerial business-driven decision-making processes and analytics research. In this sense, the current study can reveal fresh research directions and assist in identifying significant research gaps.

CONTRIBUTIONS OF CO-AUTHORS

Matendo Didas	Conceived the idea and wrote the paper
Frederick Chali	Provided technical info on methods and materials
Noe Elisa	Review of the initial paper draft

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