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# Interpreting, analyzing and distributing information: A big data framework for competitive intelligence

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**ABSTRACT** This paper aimed to develop a data-based technological innovation framework focused on the competitive intelligence process. Technological innovations increasingly transform the behavior of societies, affecting all sectors. Solutions such as cloud computing, the Internet of Things, and artificial intelligence provide and benefit from a vast generation of data: large data sets called Big Data. The use of new technologies in all sectors increases in the face of such innovation and technological mechanisms of management. We advocated that the use of Big Data and the competitive intelligence process could help generate or maintain a competitive advantage for organizations. We based the proposition of our framework on the concepts of Big Data and competitive intelligence. Our proposal is a theoretical framework for use in the collection, treatment, and distribution of information directed to strategic decision-makers. Its systematized architecture allows the integration of processes that generate information for decision making.

**KEYWORDS** Big data, competitive intelligence, technological innovation

## 1. INTRODUCTION

Innovation in its complexity adopts new social and organizational technologies as main components. The concept of "innovation" is defined as product and process technological innovation (PPT) in the 1992 and 1997 editions of the Oslo Manual, with technology being considered one of the steps leading to its implementation. Since the third edition of the manual in 2005, with the inclusion of the service sector, the term "technological" has been removed from the definitions of innovation as companies in the service sector could mistakenly interpret it as "using high-tech facilities and equipment" (OECD, 2005, p. 17). Even if the term "technological" is no longer part of the innovation concept, the interpretation makes it explicit that all innovation, in essence, is already technological (OECD, 2005).

Innovation is commonly associated with computer elements (hardware and software) that have capabilities to generate, store, process, and distribute data in large volumes, called Big Data. Its use can contribute to the discovery of new opportunities in corporative technological innovation (Li, Zhang & Hu, 2017). Data based technological innovation proves to be a process of change in the environment and management in organizations, especially if used together with the competitive intelligence process.

Competitive intelligence has been practiced along with the other support functions in companies because it brings appreciated value to the decision-maker (Vuori, 2011). It is a vital component of the planning and strategic management process, gathering data and information in a broad strategic vision context that allows the forecasting or projection of events in its competitive environment (Bose, 2008).

The context of the study involves the dynamics of technological innovations, those based on data (Big Data), and the need for efficient and safe use of the large volume of data generated in the environments of organizations. We also observed ethical components of safety and reliability when building business models (Wolfert, Ge, Verdouw & Bogaardt, 2017). The objective of this paper is to propose a framework for an integrated process of Big Data intelligence in organizations.

Previous studies discussed and highlighted Big Data and competitive intelligence approaches together, for example Hughes (2017); Calof, Richards and Santilli (2017); Rothberg and Erickson (2017); Vajjhala and Strang (2017); Erickson and Rothberg (2016); Shi, Lee and Whinston (2016); Wei et al. (2016); Bruneau and Frion (2015) and Erickson and Rothberg (2013).

Zhang et al. (2020) developed a bibliometric review about Big Data in business research and they suggested that researchers pay more attention to research topics such as decision making to leverage experience from the information management field to offer practitioners improvements in Big Data research and applications. Another suggestion is to make advancements in studies with Big Data relating to research and the field of business using interdisciplinary integration.

Our study brings innovation from a theoretical perspective by addressing an emerging theme as a new digital paradigm (Urbinati, Bogers, Chiesa & Frattini, 2019). In this paradigm, companies generate value by digitizing their services and products, and the consequent analysis of media contents becomes a key success factor in the Big Data environment (Jimenez-Marquez, Gonzalez-Carrasco, Lopez-Cuadrado & Ruiz-Mezcua, 2019). Hence, our study can spur analysts and researchers to develop tools that enable the capture, processing, and analysis of data, turning this data into actionable intelligence for decision-makers.

Organizations have different degrees of complexity, especially in relation to technological articulation and intensity. Additionally, having plenty of databases does not necessarily fit into the "Big Data" concept.

The framework has been developed in two stages. In the first stage, we explored the literature in order to identify the framework's structuring theories. These are Big Data and competitive intelligence and their relationships with technological innovation and strategic management elements. These are widely used in research in the area, resulting in knowledge management, organizational performance management, marketing strategies, production strategies, organizational processes, decision making, and the organization's resources and capabilities. In the second stage, we propose a framework, its theoretical basis, as well as its application.

## 2. THEORETICAL BACKGROUND

### 2.1 2.1. Big Data

Information and communication technologies have provided, through evolution and application, huge impacts on society and the economy, especially in the last three decades. The changes provided by the adoption of these technologies are evident and continue to present opportunities and challenges, such as in the case of Big Data (Sonka, 2014).

Big Data has been described in different ways throughout its development and consolidation. The Apache Hadoop platform defined it in 2010 as "datasets which could not be captured, managed, and processed by general computers within an acceptable scope." (Chen, Mao & Liu, 2014, p. 173).

McKinsey & Company describes Big Data as the next frontier for innovation, competition, and productivity (Manyika et al., 2011). A comparative study by the International Data Corporation (IDC) descfibe it as "a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high-velocity capture, discovery, and/or analysis." (Gantz & Reinsel, 2011, p. 6).

Other authors have considered it to be "a set of techniques and technologies that require new forms of integration to uncover large hidden values from large datasets that are diverse, complex, and of a massive scale." (Hashem et al., 2015, p. 100).

From a managerial perspective, it is relevant to highlight that Big Data provides managers with access to information and generates subsidies to the ability of decision making (Sonka, 2014). The promise and value of Big Data go far beyond what is known, and have limitations only in their capabilities and human resources.

According to the IDC definition, the characteristics of Big Data may be described by the 4Vs (volume, variety, velocity, and value) which are also used by Hashem et al. (2015), Sonka (2014), and Gomes and Braga (2017). The classification into five aspects to better understand the 4Vs is significant because of the large-scale data in the cloud. These are data sources, content format, data storage, data preparation, and data processing (Hashem et al., 2015).

Such characteristics and classification allow us to consider Big Data as an innovation, because it meets the definitions proposed by Freeman, Clark and Soete (1982), Senge (1997), and O'Sullivan and Dooley (2008). They introduce a new way of generating, processing, and making information available so it can be replicated infinitely at acceptable costs and can be exploited for both personal and organizational benefit to add value.

The advent of Big Data establishes itself as a development of technological innovation relating to other innovations such as cloud computing and the internet of things (IoT). With the first one, this is because the development of cloud computing offers solutions for the storage and processing of massive volume data sets. With IoT, this is because they are two interdependent technologies that must be developed together since the dissemination of IoT leverages the growth of data by categories and quantities, allowing the application and development of data (Chen, Mao & Liu, 2014).

We have added this relationship to artificial intelligence, as it also deals with increasing volume, velocity, and variety of data, allowing the delegation of hard recognition and learning patterns and other tasks to computer-based approaches (O'Leary, 2013).

We highlight that the context of Big Data and related technologies bring with them the uncertainties of security, or insecurity, on the part of the agents and especially individuals when they make their data available and maintain, in some way, some or all control over its use (Tene & Polonetsky, 2012).

Compliance with legal principles can be a detriment to competitiveness since it can generate a competitive advantage or disadvantage depending on the mode of use and attention to them. It can be detrimental if a company or institution does not accommodate the legal environment that extends beyond the limits of a given territory.

## 2.2 Competitive Intelligence

The definition of competitive intelligence encompasses two vital concepts for the business environment. First is the meaning of "competitive", which refers to processes that involve competition between at least two agents. Second is the concept of "corporate intelligence", defined as an ability to predict possible changes in a future temporal universe and prepare for an intervention, a process in which the parties use the operating environment to collect data, information, or knowledge in decision making and then implement actions (Breakspear, 2013; Köseoglu, Ross & Okumus, 2016).

The competitive intelligence concept has been studied in the field of management in several areas of strategic administration, and it is common to use other names that sometimes cause confusion between the terms. The majority of them occur in relation to the distinction of the competitive intelligence business. Many uses these terms as synonyms, linking business intelligence to the information technology companies and describing it as the set of tools that allow the generation of information in business environments such as data warehouses, data mining, CRM, and OLAP tools, among others (ABRAIC, 2012). Competitive intelligence refers to a broader process, encompassing the obtaining and processing of information that comes from networks maintained by competitive intelligence systems in which the business intelligence information is inserted (ABRAIC, 2012).

Considering competitive intelligence as a process and a product at the same time has its roots in the assumption that the more one understands the strengths and weaknesses of competitors, the better the conditions to formulate an effective strategy are. Competitive intelligence is, first, an analytical process of transforming disaggregated data into usable strategic knowledge about competitors' intentions, capabilities, performance, and positioning; and, second, a result of this process as a final product (Bernhardt, 1994).

The competitive intelligence process results in information that generates recommendations for future events, in addition to reports that justify past decisions in decision making (Gomes & Braga, 2017). In the search for information in the competitive environment, companies may not find clear answers to develop their strategies. For the correct articulation of competitive intelligence activities, the United States Central Intelligence Agency (CIA) described a cyclical process of five interdependent phases: planning and direction, collection, processing, analysis, and production and dissemination (Bernhardt, 1994). Competitive intelligence is both a process and a product (intelligence) (Bernhardt, 1994). An effective competitive intelligence process, supported by the Society of Competitive Intelligence Professionals (SCIP), is executed in a continuous cycle, called the competitive intelligence cycle.

The cycle is a process in which information is collected, evaluated, analyzed, processed, and made available as intelligence for use in decision making, consisting of planning and direction, collection, analysis, dissemination, and feedback (Bose, 2008). This cycle is an update of Bernhardt's (1994) initial model, in which processing, analysis, and production are all grouped in phase three (analysis), phase four includes distribution, and finally, insertion of feedback is found in phase five. Previously, Bose (2008), Calof, and Dishman (2002) presented a five-phase model for competitive intelligence, in which the fifth phase consists of decision making. The difference between the models demonstrated by Calof and Dishman (2002) and Bose (2008) is only semantic if only phases one to four are considered. However, phase five differs, as Calof and Dishman (2002) defines phase five as decision making, while Bose (2008), defines it as feedback. However, this difference can be mitigated by considering that the decision-making process results in feedback to the competitive intelligence system. In this way, it can be considered that both process are included in the same phase.

Besides the five-stage models proposed by Bernhardt (1994a), Calof and Dishman (2002), and Bose (2008), Fleisher (2004) and Brummer, Badenhorst, and Neuland (2006) presented a four-stage model. Moreover, De Pelsmacker et al. (2005) and Nasri (2011) have outlined processes with six stages: planning and focus, collection, analysis, communication, process/structure, and organizational awareness/culture.

Keiser's previous study (1987) presented a six-stage model, consisting of the definition of rivals, data that better define them, specific sources to be researched, classification of these sources and delimitation of a cooperation strategy in the information collection, blending and analysis of the information, and monitoring of the rivals according to the results coming from the information sources (Köseoglu, Ross & Okumus, 2016).

Köseoglu, Ross, and Okumus (2016) used contributions from Brummer, Badenhorst, and Neuland (2006) by inserting four elements to support the construction of the process in the planning and steering stage of the Bernhardt (1994) model. These include intelligence users and decision-makers, other users, data needs, and the key intelligence topics (KITs), developed by Herring (1999). We chose the

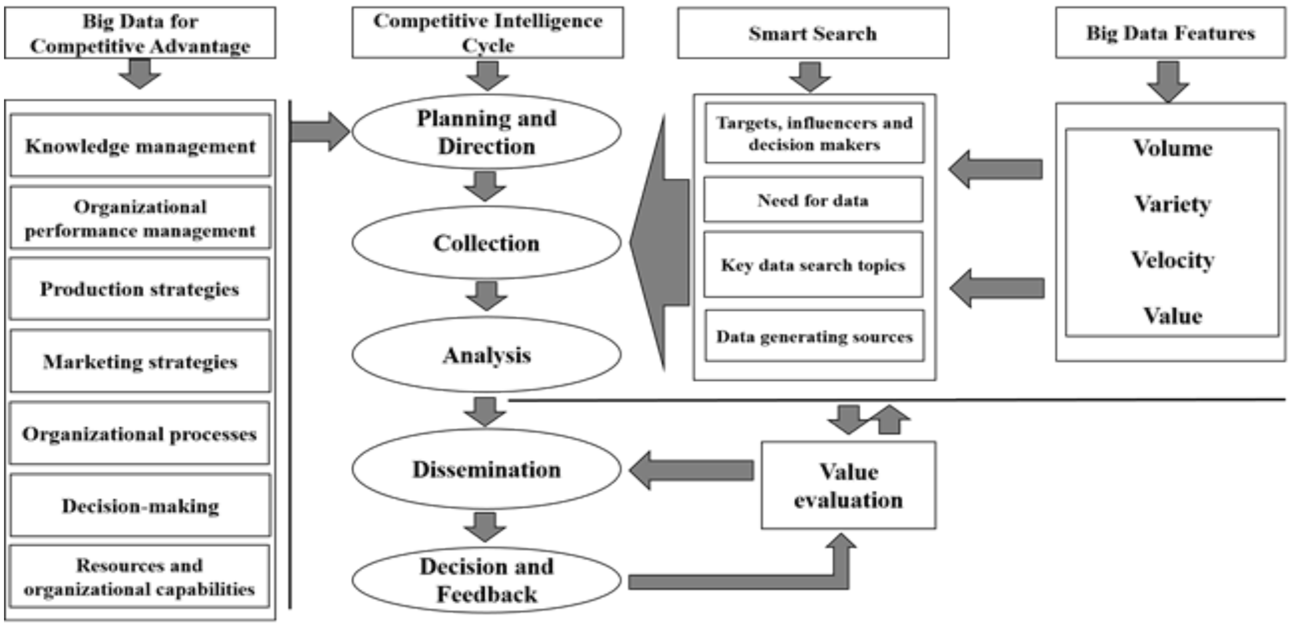


*Figure 1* Big Data Intelligence Integrated Process (BDIIP).

model proposed by Köseoglu, Ross, and Okumus (2016) to serve as a reference for our framework proposal.

## 3. FRAMEWORK PROPOSAL

Our proposal is presented in two parts. The first, the Big Data Intelligence Integrated Process (BDIIP, Figure 1), is based on the competitive intelligence cycle of Bose (2008), however, in the fifth phase we also consider the decision-making suggested by Calof and Dishman (2002), the characteristics of Big Data (4Vs) of Chen, Mao and Liu (2014), and we include variables of Brummer, Badenhorst, and Neuland (2006) later adopted by Köseoglu, Ross and Okumus (2016). In the second part, we present the Big Data Intelligence Framework - BDIF (Figure 2), based on the theoretical interpretation of BDIIP.

Our framework is supported by five points of interest essential for its definition: 1) who are the actors that effectively are the potential targets, influencers, and/or decision-makers to define the profile and market positioning?, 2) what is the real need for data?, 3) definition of the key-topics for searching, 4) what are the main generating sources and which kinds of data should be mined from the ones available?, and 5) definition of a Big Data intelligent searching cycle from the key-elements of the competitive intelligence cycle, validated by the elements characterized as Big Data (4V).

Subsequently, each of these points will be contextualized. Additionally, the Big Data tools allow the analysis itself to identify the relevant descriptors in the information.

*1) Main potential targets, influencers, and/or decision-makers* and *2) data needs*: first, as a characteristic of Big Data, the large volume of data is often presented in different ways for the same purpose. As such, redundancy and the noise level are problems that must be followed-up and minimized to improve data performance. Such characteristics are, for example, enhanced by the structure of data in relational databases and also by data generated via IoT (Chen, Mao & Liu, 2014; Hashem et al., 2015).

As well as prior knowledge of the types of data required, knowing the users, or clearly defining them, is a key-point in the search for the information needed for the intelligence process (Bose, 2008). This is fundamental for planning the process of collecting and analyzing data to convert them into useful information (Oliveira, 2013).

Within the competitive intelligence process, the users of the information need to be previously known and defined, as this is essentially an internal process.

In practice, we suggested using Big Data to identify the decision-makers, users, or influencers in a given business environment and what kind of information is used or

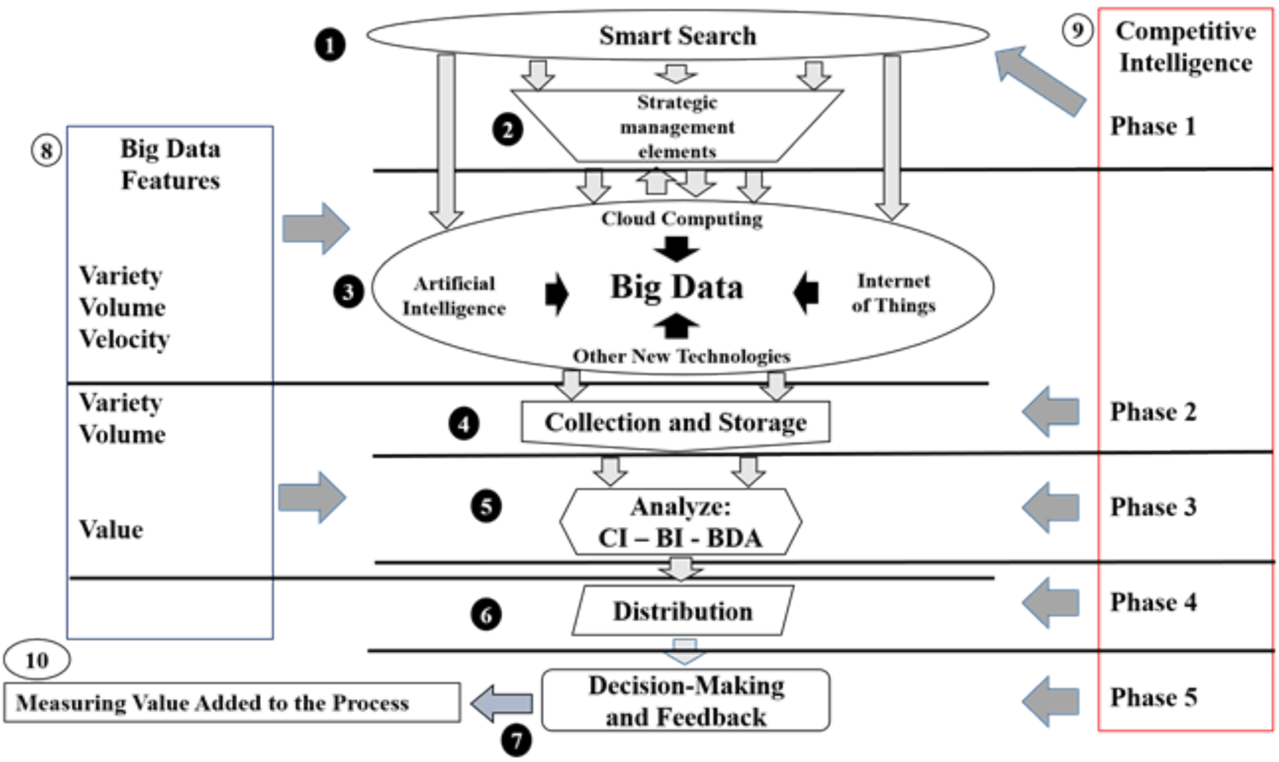


*Figure 2 Big Data Intelligence Framework (BDIF).*

disseminated by them, in the environment outside the organization.

*3) Definition of key topics for searching:* key intelligence topics (KITs) are used to improve the planning of competitive intelligence process activities. These topics have been previously defined by intelligence users and analysts, and segmented into three functional categories: strategic decisions and actions, early warning topics, and description of the main competitors in the business environment (Herring, 1999).

In the traditional competitive intelligence process, the identification of the topics related to the main competitors and market conditions is the last stage of the definition. However, in the process that we propose, it will be used as the main instrument to identify opportunities and risks in an environment and, from this information, start the generation of the intelligence process based on Big Data.

We suggest Big Data tools to monitor the market, reversing the definition of the main topic processes by the users for Big Data analysis, mainly using unstructured data. This includes, for example, data analysis or text mining.

*4) Generating sources and data availability:* data sources may be classified as social media, machine-generated, detection, transactional data, and IoT (Hashem et al., 2015). The different source availability provided by the Big Data environment allows a vast range of searches. However, unstructured data represents a great challenge, since in some cases this type of data does not undergo a prior evaluation as to its authenticity and validity. These are subject to a lack of veracity or credibility. This is unlike structured data from official or better-known databases, which may contain errors, distortions, or lack updates, yet is still in some way "certified" by the publishers.

We propose that operationalization in an autonomous way verifies the ethical and legal veracity and viability of the use of this data. That certifies or minimizes the choice of the bases since the ownership and privacy in the universe of Big Data represent a big challenge. However, many of these challenges have their origins in technical issues and are based on the legislation and organizational aspects that can be met by technical measures, a prerequisite that allows analysis without binding the user's identity (Jensen, 2013).

*5) Valuation of the Big Data intelligent searching cycle:* valuation occurs from the key-elements of the competitive intelligence cycle, its final evaluation, and verification of the principles of collection, treatment, and distribution of data and information. By meeting ethical standards of privacy, use, and tenure rights, they consider the definition of competitive intelligence as a systematic and continuous business process to collect, ethically and legally, information about targets in the business environment (Shaker & Gembicki, 1999) and mainly disconnected from the association to corporate espionage. Ethical and moral conduct is a significant part of the strategic process (Köseoglu, Ross & Okumus, 2016) and also is essential to meet the ethical demands on the asymmetry of power concerning the domain of information between users and large corporations. The validation done by attributing values such as trust and transparency gives credibility to the use of the tool in the generation of knowledge and intelligence (Carbonell, 2016).

So far, the searching process integrates the concepts and principles of competitive intelligence and Big Data, particularly regarding the searching, processing, and transformation of data into actionable information. In certain aspects, it is similar to processes already used for obtaining and producing information. For this purpose, the tenet for using it takes into consideration the tasks of the process, integrated within a broader context, such as in laboratories, centers, or information production and distribution cores. In organizations, the Big Data Intelligence Integrated Process (BDIIP) may be used as an operationalization structure for data/information capturing, storing, processing, and distribution in intelligence operational centers.

It is not a closed-system process, but a cluster of processes with integrated operation platforms for adding value to available data and/or produced for specific analysis originating from several interfaces that possibly require analysis and operation with diverse resources and knowledge.

It is also an organic framework susceptible to inferences and interference according to the needs of the organization at a given time. The framework is based on the management area, defined as strategic management elements, and contextualized in knowledge management, organizational performance management, marketing strategies, production strategies, organizational processes, resources and capabilities of the organization, and decision making.

Given their characteristics, we consider that the elements are not static as they can move to a multidisciplinary scope, adding other factors and subjects to meet a determined demand such as the price analysis of a given product, in a business environment, by the production or marketing strategic vision linked to explanatory or predictive statistical analysis.

The process explores the main characteristics of Big Data defined as the 4Vs presented and discussed by Chen, Mao and Liu (2014) and the elements of the competitive intelligence cycle proposed by Bose (2008) and Calof and Dishman (2002), which allowed the development of the Big Data Intelligence Framework (BDIF; Figure 2).

Our proposal has resulted in the construction of the Big Data Intelligence Integrated Process (BDIIP; Figure 1) considering the following fundamentals, as presented in Figure 2:

*1) Intelligent search:* contemplates phase 1 with planning and direction of the competitive intelligence cycle, according to Bose (2008). In this phase, the pre-phase elements were adapted from Köseoglu, Ross, and Okumus (2016) to the BDIIP (Figure 1). They consist of targets, influencers, decision-makers, data needs, key-topics of searching (Herring, 1999), and generating sources of data. In order to sustain and improve the decision-making process, it is necessary to fit it into a relevant strategic context for the business to be able to answer essential questions (Bernhardt, 1994; Oliveira, 2013).

That is the data search for effective planning in the Big Data universe, whereas the objectives are determined, and it is defined which methodology to seek. The integrated process differs from the competitive intelligence process as it can meet several demands simultaneously or one problem in several ways, while competitive intelligence focuses on one problem at a time. This stage of the framework does not contemplate Big Data that is only about definitions which may or may not be executed in large databases.

*2) Strategic elements of management:* these are also part of phase 1 of competitive intelligence. They consist of the disciplinary filter of the search process since the use of Big Data or its analysis can be an instrument for maintenance or generation of advantage. This filter should preferably be applied and integrated into the search engine so that the results are objective and targeted. However, it can be applied manually *a posteriori*, which means the analyst applies the filter according to the interest or need after data collection. The definitions of strategic elements of management may be adapted accordingly to specific needs. The adoption of the term "strategic elements of management" is only a representation used to define this phase that does not restrict a broader use of content, practices, and processes in the management area that can lead to the development of a specific project, and can be replaced by emerging theories and new holistic proposals.

*3) Big Data universe and related technologies:* these include cloud computing, IoT, artificial intelligence, and other new technologies that emerge in this scenario. This phase covers the foundations of Big Data and all the complexity of the very definition of the term Big Data with its characteristics, classification, and challenges. This includes, for example, the adequacy of researchers and entities to follow data protection laws. In this stage of the framework, there are three characteristic elements of Big Data: volume, variety, and velocity defined by Hashem et al. (2015), Sonka (2014), and Gomes and Braga (2017). This is in addition to the classifications of data sources (social media, machine-generated, detection, transactional data, and sensorization) and format and content (structured, semi-structured and unstructured) (Hashem et al., 2015). The volume refers to the enormous amount of data generated in large databases and media almost instantly, allowing the use of data-mining to identify sources of intelligence generation. The dedicated data, such as sensor measurements (IoT) and the use of artificial intelligence, are in the early stages but with future potential for integrated use. Variety deals with different types of collected data that include video, image, text, audio, and structured or unstructured data. As a dimension of Big Data, it deals with the concept of data that expand into different formats. Velocity represents the ability to generate data in real-time and rapid dissemination (Hashem et al., 2015). The velocity has a significant impact on the performance of business innovation actions, as it is necessary to quickly integrate different types of data in a timely manner to generate efficiency and effectiveness in the process (Ghasemaghaei & Calic, 2020).

*4) Collection and storage:* we contemplate phase 2 of the competitive intelligence cycle

(BOSE, 2008) and the variety of characteristics and the volume of Big Data. This also meets the need for "data storage" classification and its tasks: documentation, guidance, graph, and value. These are forms of data preparation: cleaning, normalization, and transformation (Hashem et al., 2015).

*5) Analysis:* this contemplates phase 3 of competitive intelligence and the value characteristic of Big Data. It refers to the process of discovering the hidden values of large data sets with various types and fast generation (Hashem et al., 2015). Although the presence of volume and variety characteristics are inherent, the value designation begins to be reasoned on the quality of the data analysis. For this, they rely on the use of competitive intelligence analysis techniques, business intelligence, and Big Data analysis, as well as supporting tools for decision making. At this stage, the analyst's expertise improves the use of this tool and the generation of results. Depending on the project and, especially, the way the results are disseminated, this is the last stage of Big Data. The probability is that the information for decision making is passed on even if using data in a way that could not be considered Big Data conceptually, only data transmitting the information. The distribution of this information, in competitive intelligence publications, is approached as the idea of producing actionable intelligence, with the primary role of modeling and influencing strategic thinking by interlocution between analysts and management (Gilad, 2016).

*6) Distribution:* this contemplates phase 4 (distribution) of Bose's intelligence cycle (2008). It follows the same pattern of information distribution as competitive intelligence, which means information is disseminated directly to interest groups through publications, meetings, lectures, and field activities, among other traditional forms. However, an organization's intelligence department may also adhere to the use of platforms and applications to increase the interaction and use of information. Depending on the application architecture, it may or may not be considered Big Data.

*7) Decision:* the final phase of the competitive intelligence cycle. The information, once made available, may or may not be used in decision making. In this phase, the involvement of intelligence analysts with other organizations' members will be decisive in adding value to the competitive intelligence process as a whole, as well as in directing the actions of the organization. All members' interactions can be measured through feedback, which will also serve as inputs for the re-start of the intelligence process.

*8) Description of Big Data Characteristics:* according to Hashem et al. (2015) and other previously cited authors.

*9) Description of the competitive intelligence cycle:* according to Bose (2008), Calof and Dishman (2002) and other previously cited authors.

*10) Validation or Valuation:* The final step of the framework measures the utility of the process for decision making. We consider "value" to be interpreted as "veracity" (Gomes & Braga, 2017), unlike the "v" value in Big Data. The process, understood as a cycle, has its beginning for a question-less purpose or analysis in which many factors and resources (human, financial, temporal, and technological) were committed for the benefit of the project. The final characteristic of the information generated should be measured by its capacity to enable better decision making. The higher the quality or veracity, the greater the value of the process. The metrics for this evaluation should be defined in each project in phase 1 of the competitive intelligence cycle. The returns may also be gauges of the quality of the actionable information developed by the organization's intelligence department.

## 4. DISCUSSION

We understand that Big Data, through new technologies such as social media and IoT, enables organizations to develop innovative business models and products considering three dimensions for decision making and gaining advantages: creative use of technology and Big Data, unlocking innovation through collaboration and co-creation, and sustainability agendas (Nudurupati, Tebboune & Hardman, 2016).

Using Big Data together with the organization's capabilities and resources can lead to advantages in the business environment. The importance of human skills and intangible resources associated with learning and organizational culture creates a specific capacity for the corporation. Perhaps it is unlikely that Big Data alone can generate or maintain any advantage for the organization (Gupta & George, 2016).

Big Data can be considered a new element capable of producing competitive differentials, provided it is handled with intelligence and adequate tools, observing its characteristics of velocity and variety. However, the generation of massive data volume, variety, and velocity does not guarantee the best decision-making or obtaining any advantage, and for this, it is necessary to extract its most fundamental characteristic in the process: the value generation. Big Data provides the opportunity to collect and integrate various datasets for the identification and extraction of information used to improve decision making (Ayankoya, Greyling & Calitz, 2016).

For organizational goals to be achieved, using Big Data is important to understand how each of its characteristics affect the results to allocate them in the best way. This is a key task to improve performance (Ghasemaghaei & Calic, 2020).

We highlight that the universe of Big Data associated with cloud computing, IoT, and artificial intelligence transforms management systems. However, having a large volume of data does not necessarily guarantee that you have the right information at the right time.

Big Data, combined with sophisticated business analysis tools, has the potential to provide companies with insights into customer and market behavior, enabling faster and more effective data-driven decision making (Kelly, 2014). Therefore, the introduction of competitive intelligence works as a strategic tool to manage and process raw information and turn it into useful information at the right time, targeting the decision-maker.

The adoption of intelligence in the Big Data strategic processes changes the environment because the adoption of competitive intelligence tools such as business intelligence and Big Data analytics streamlines actions, interpretation, and the consequent generation of information in the form of actionable intelligence.

Special attention should be given to the fact that the speed of changes, uncertainties, and complexity of competitive environments impose on analysts and decision-makers a pressure for assertiveness, reinforcing the importance of adopting competitive intelligence as a flexible and adaptable approach (Mohammadalian, Nazemi & Tarokh, 2013).

The developed framework considers the interactions of human resources and their capabilities for interpretation, analysis, and distribution of information in the form of intelligence. It was developed to be used in the core of organizational intelligence, which uses the business intelligence resources and expertise of its researchers and analysts. This conception is justified because "big organizations have implemented Big Data adoption and development for business value creations through the result of Big Data analytics applications" (Adrian, Abdullah, Atan & Jusoh, 2016, p. 174). Organizations with different purposes and large corporations can help the members of the decision-making process with information without requiring an economic counterpart.

We understand that Big Data, associated with an intelligence process, is a source of some advantage. However, there is a need to combine people, tools, management, data-oriented culture development, and human skills to obtain this advantage (Kabir & Carayannis, 2013).

We also emphasize that by adopting advanced analysis technologies, organizations can make use of essential data for the development of innovative insights into products and services (Günther et al., 2017). We reinforce the adoption of new technologies as a process given the need to prepare data capture and processing architectures, as well as the time needed to generate databases that represent Big Data in its essence. However, as the framework allows for interaction and fragmentation, such fragments can be executed in the form of specific projects for information analysis and process execution sharing. The adoption of new technologies allows the use of partners to perform tasks that are beyond the physical and technical capacity of the organization. The framework grants interactions between companies and analyst partners for the production of information that can be disseminated in order to generate better results and extract value from the data and the process that allows better decision making.

## 5. FINAL CONSIDERATIONS, REMARKS, AND LIMITATIONS

The huge development in technological innovations influences and transforms social and commercial relationships and significantly alters productive environments. This context served as a premise for our proposal. We started from one which, using large data sets (Big Data) together with the competitive intelligence process, can improve decision making and, consequently, maintain, or generate some advantage for organizations.

Our study brings contributions and innovations when considering the use of Big Data integrated into the theory of competitive intelligence. It presents the ability to generate information for the decision-making process from the use of new technologies for data generation, storage, and integration. Our proposal of the Big Data Intelligence Framework (BDIF) demonstrates the capacity of data collection in the processing and distribution of information that can be used as a reference for the systematic construction of intelligence cores.

As limitations of the proposal, we recognize that an intelligence core alone may not be able to generate all the data to produce the necessary knowledge to be made available, as well as for the transmission of information. It is essential to build cooperative relationships through commercial or other partnerships.

For future research, we propose implementing BDIF for the formation of the intelligence core in organizations or other interest groups. Further, the continuity of tests with the practical and theoretical application of the Big Data Intelligence Integrated Process (BDIIP), developing targeted studies is possible.

We also highlight, in relation to the practical application, the possibility of developing integrated field tools to initialize the use of the framework and disseminate the content appropriately at the right time, as well as new studies for the proposition and realization of value. Finally, we considered that the generation of information for the intelligence process, with the ability to create a variety of advantages for the organization through technological innovations such as Big Data, starts from the premise that human capacity has to define the types of data, making the human capacity the defining factor of information quality (human perception of value). The whole process of generating knowledge is the result of an algorithmic reaction, or a succession of steps, including emotional components, that lead to a determined final result.

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