Big data as a value generator in decision support systems: a literature review

Gustavo Grander and Luciano Ferreira da Silva
PPGP, Universidade Nove de Julho, Sao Paulo, Brazil, and
Ernesto Del Rosário Santibañez Gonzalez
Universidad de Talca, Talca, Chile

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Abstract

Purpose – This paper aims to analyze how decision support systems manage Big data to obtain value.
Design/methodology/approach – A systematic literature review was performed with screening and analysis of 72 articles published between 2012 and 2019.
Findings – The findings reveal that techniques of big data analytics, machine learning algorithms and technologies predominantly related to computer science and cloud computing are used on decision support systems. Another finding was that the main areas that these techniques and technologies are been applied are logistic, traffic, health, business and market. This article also allows authors to understand the relationship in which descriptive, predictive and prescriptive analyses are used according to an inverse relationship of complexity in data analysis and the need for human decision-making.
Originality/value – As it is an emerging theme, this study seeks to present an overview of the techniques and technologies that are being discussed in the literature to solve problems in their respective areas, as a form of theoretical contribution. The authors also understand that there is a practical contribution to the maturity of the discussion and with reflections even presented as suggestions for future research, such as the ethical discussion. This study's descriptive classification can also serve as a guide for new researchers who seek to understand the research involving decision support systems and big data to gain value in our society.

Keywords Decision support systems, Big data, Machine learning, Analytics, Cloud computing, Algorithm
Paper type Literature review

1. Introduction

While Big Data can be used as a powerful tool to treat various social diseases, offering the potential for new insights into areas such as medical research, counterterrorism and climate change, its use also allows invasions of privacy, diminished civil liberties and increased state and corporate control (Boyd & Crawford, 2012). There is a big challenge in managing Big data due to the increasing and cheap volume of data storage (Demirkan & Delen, 2013).

Most data sets from which scientists and researchers have been able to extract real meaning are still very small compared to the proportion of data that can be captured (Dobre & Xhafa, 2014). Big data analysis should include the phases of data generation, acquisition, storage and analysis and can provide useful values at each stage through judgments, suggestions, support or decisions (Chen, Mao & Liu, 2014a). Some authors point out that

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advances in analytical techniques, especially machine learning, have been a major facilitator for dealing with large data set analysis (Murdoch & Detsky, 2013).

Big data are defined as a large set of data that are difficult to store, process analyze and understand using traditional database processing tools (Huang & Chaovalitwongse, 2015), Big data emerge as a paradigm shift in how organizations make decisions (Mortenson, Doherty & Robinson, 2015). Therefore, through decision support systems (DSS), it is possible to process large volumes of data using output models with accessible interfaces (Constantiou & Kallinikos, 2014). Research in big data and DSS has presented technological aspects and big data design challenges as the main focus (Chen, Mao, Zhang & Leung, 2014b).

We, therefore, have the opportunity to propose an in-depth analysis of how DSS manages big data to obtain value. In this context, we performed a systematic literature review (SLR) of the use of big data in DSS. To achieve this goal, we propose to answer two questions: DSS manages big data to obtain value which techniques and technologies? And, DSS has been applied to solve what types of problems? To answer the research questions, we conducted an SLR with research in the academic databases Scopus and Web of Science (WoS), in August 2019.

As a contribution of our study, we show that DSS is used for the management of big data mainly through techniques such as big data analytics (BDA), machine learning algorithms and technologies such as cloud computing. The main areas in which these techniques and technologies are applied are logistics, traffic, health, organization and market.

This article is structured as follows: In addition to this Introduction section, we present in Section 2 the methodological procedures applied in the research, the results are presented in Section 3, discussions in Section 4 and in Section 5, we present the conclusion of our study.

2. Methodology

We performed the SLR based on the guidelines suggested by Petticrew & Roberts (2006) to understand the use of big data in DSS. We have chosen to develop an SLR because of the rigor of the research methodology that involves systematic data collection procedures, descriptive and qualitative data analysis techniques.

2.1 Data collection

First, we start with the identification phase with the application of a search string, initially based on preliminary searches. Then, we apply the string to the database search tools in order to identify other ways in which the searched terms are referenced (Petticrew & Roberts, 2006). Thus, after a few rounds of searching, new terms were identified and added to the initial string to obtain a corpus of analysis. Therefore, the first stage of the SLR consisted of searching the Scopus and WoS databases, using the following Boolean terms: "Big Data" AND ("Decision Theory" or "decision support system*" or "decision-support system*"). The use of the asterisk (*) in the search string serves to obtain variations of words in their plural form.

The second stage of the SLR had as criteria the filter by areas. The Scopus database was restricted to the following areas: business, management and accounting; decision sciences; social sciences. The WoS base was restricted to the following areas: business, management and social science interdisciplinary.

The third stage of the SLR consisted of filtering the databases keeping only articles, thereby excluding books, reviews, etc. The fourth step of SRL consisted of checking the availability of downloadable articles. The fifth stage of the SLR was reading the articles and checking their alignment with the research objective; articles without objective strongly dealing with the subject were considered inappropriate for the analysis, and therefore, they

were excluded from the sample. The sixth stage of the SLR consisted of identifying repeated articles and consequently reducing duplication. Finally, the seventh stage of SLR was the consolidation of the two bases for an in-depth analysis of the articles. The exclusion flow of articles is presented in Table 1.

The initial search totaled 1,427 documents contained in both databases, and at the end of the seven steps, 5% of the sample, 72 articles, were considered adequate for full reading and analysis.

2.2 Data analysis

We performed the SLR of the 72 selected articles, of which 63 were empirical and 9 were theoretical. The articles were read in full and classified in a spreadsheet according to relationships identified throughout the analysis and that met the research questions. We note that the first record refers to the year 2012, and until 2018, there is a growth in the number of publications. The year 2019 had eight publications, but due to the date of the search in the databases, it was not possible to account for the total number of publications in the year (Table 2).

Regarding the analysis process, after selecting and collecting the database, the researchers started categorizing the contents from a qualitative perspective (Petticrew & Roberts, 2008). A recursive process was applied based on reflective critical reading and classification of the content according to its adherence to the themes proposed in this research. The process of an SLR must allow its transparency and replicability as pointed out by Tranfield, Denyer & Smart (2003). The following are the results of this study and their respective analyzes.

3. Results

To answer the first research question, we classified the articles into two groups: The first group deals with techniques, and the second group with technologies. There is a wide variety of techniques and technologies for capturing, selecting, analyzing and visualizing big data, and these tools focus on three classes: batch processing, flow processing and interactive analysis tools (Chen & Zhang, 2014).

3.1 Techniques applied in big data

The items presented here are related to the application of data analysis techniques to obtain value from big data.

Stage	Criteria	Scopus	WoS
1	Survey string search	1,087 documents	340 documents
2	Filter by area	257 documents	25 documents
3	Filter by articles	98 articles	15 articles
4	Exclusion unavailable articles	88 articles	13 articles
5	Exclusion inappropriate articles	71 articles	10 articles
6	Articles in both bases	9 articles	
7	Total articles analyzed in the review	72 articles	

Table 1. Exclusion flow of articles

Year	2012	2013	2014	2015	2016	2017	2018	2019
Quantity of paper	1	1	3	8	14	14	23	8

Table 2. Quantity of papers according to years

3.1.1 Machine learning technique with supervised learning algorithm. Classification algorithms from this group were used, for example, as a management tool for the creation of a DSS that enabled credit risk assessment in the financial market (Hayashi, 2016), for building modernization assessment allowing the decision-maker to select the best alternatives in terms of energy consumption and installation cost (Rasiulis, Ustinovichius, Vilutiene & Popov, 2016), to deal with business data heterogeneity and multidimensionality (Nimmagadda, Reiners & Wood, 2018). We also found application in route optimization models through DSS to view traffic volume and weather interactions applicable to transport planners, traffic control rooms and urban infrastructure DSS (Sathiaraj, Punkasem, Wang & Seedah, 2018) and through an online route generation system with Dijkstra algorithm, which resulted in changes of route paradigms that were determined together (Rönnqvist, Svenson, Flisberg & Jö). Finally, we found an application for the purpose of identifying and predicting social issues through online news analytics (Suh, 2019).

Other findings were with vector machine for decision-making optimization through patient similarity (Tashkandi, Wiese & Wiese, 2018) and in optimizing data collection for cancer classification and online critic sentiments (Ghaddar & Naoum-Sawaya, 2018), the fuzzy rule to determine the health status of cattle to predict nutritional intake (Sivamani, Choi & Cho, 2018), Mehrabian–Russell model for forecasting consumer purchases using climate parameters (Tian, Zhang & Zhang, 2018), the use of a set of attribute reduction and data set analysis in information systems (Li, Yang, Jin & Guo, 2017) and rapid safety feedback used to identify child maltreatment (Gillingham, 2019a).

We have identified that techniques applied in the above studies were for predictive data analysis, which helps anticipate changes based on understanding patterns and anomalies within a database (Hurwitz & Kirsch, 2018).

The second group of articles in our technique analysis was linear regression that has been observed in stock market index prediction studies (Khan *et al.*, 2018), in DSS for collaborative logistics networks (Ilie-Zudor *et al.*, 2015) and in predicting fuel consumption based on driving behaviors (Hsu, Lim & Yang, 2017). The least absolute shrinkage operator regression was used to estimate risk-adjusted performance in hospitals (Feuerriegel, 2016), for forecasting electricity prices based on historical data and analysis of weather conditions (Ludwig, Feuerriegel & Neumann, 2015) and for predicting population health indices from social media data to improve predictive performance (Nguyen *et al.*, 2017).

Regression of neural networks was applied to estimate rail integrity conditions to assist in maintenance control (Jamshidi *et al.*, 2018), through regression for multipurpose utility analysis, a methodology was developed to analyze resource scarcity problems in rural transport management (Chen, Achtari, Majkut & Sheu, 2017), and a regression tree model was used to quantify and optimize leak detection on the shop floor (Stein, Meller & Flath, 2018).

In this group of articles, we note the predominance of predictive data analysis. However, one article analyzed data also with prescriptive analysis (Stein *et al.*, 2018), and in which case, the results obtained by prescriptive analysis stood out in relation to predictive results. Prescriptive analyses are required to determine and evaluate alternative decisions involving objectives and requirements characterized by high volume and complexity (Wang, Gunasekaran, Ngai & Papadopoulos, 2016).

Based on these studies and on the condition of predicting situations, the value built from the use of big data in decision-making is the ability of decision-makers to allocate resources, make adjustments in their process or even to direct assertive actions to deal with child abuse as in case of Gillingham's (2019a) study. The ability to relate several factors from the big data analysis allows improving decision-making considerably; in this group, the gains also come from saving resources that can be applied in certain activities, for example, in the measurement of risks.

3.1.2 Machine learning technique with unsupervised learning algorithm. We have identified the application of cluster learning with image-based information visualization technique for

analyzing emerging data sets from the air traffic control domain (Hurter, Conversy, Gianazza & Telea, 2014), and hierarchical clustering technique used as DSS to identify near real-time industrial clusters (Papagiannidis, See-To, Assimakopoulos & Yang, 2018).

We also identified articles developed through the diffuse adaptive minimum spanning tree method that offered opportunities for the development of intelligent tourism DSS for government policymaking (Gao, Zhang, Lu, Wu & Du, 2018), P-DBSCAN algorithm that identifies areas of high photographic activity, using the information on the number of tourists providing photos and the number of photos sent to find groups at popular tourist sites (Miah, Vu, Gammack & McGrath, 2017) and user behavior map analysis through image recognition algorithms that enable tourism scenario formulation conditions for marketing strategies (Giglio, Bertacchini, Bilotta & Pantano, 2019).

In this group, again predictive analyzes formed the majority of articles, however, Hurter *et al.* (2014) conducted a study through descriptive data analysis. Descriptive analyses help to understand the historical data set and then to understand the current reality (Hurwitz & Kirsch, 2018).

Another identified group was unsupervised association learning. We have found the use of transmissible comorbidity map for patient monitoring according to risk profiles (Capobianco & Liò, 2015) and the use of sentiment analysis mechanisms that benefit from grammar-based linguistic analysis to predict stock market index trends (Chan & Chong, 2017). Both articles appropriated the decision tree as a technique and treated the data for predictive analysis.

This group of techniques and applications allows for real-time monitoring, which brings benefits and diagnostic capacity. Based on this application, decision-makers can have more agility in raising problems and opportunities organically and evolutionarily.

3.1.3 Machine learning technique with semi-supervised learning algorithm. We have only identified one article that used semi-supervised classification learning as a technique to address a Twitter user opinion rating issue in discussions from other people's retweets, using the label propagation technique for predictive analytics (Li, Li & Zhu, 2016).

3.1.4 Machine learning techniques with reinforcement learning algorithms. Studies classified as reinforcement learning have in common the traffic optimization ratio to avoid congestion during the journey. A car tracking model based on approximate set theory data was used to consider the hidden information in a field data set (Hao, Yang & Shi, 2018), and a proactive method of controlling traffic congestion with the use of deep belief network has been applied to eliminate unwanted future states (Wang, Geng & Gao, 2018b). Both studies presented a predictive analysis of data.

3.1.5 Data mining techniques. The articles emphasized the added value resulting from the use of big data in the treatment of heterogeneous data sources accessed by crisis management frameworks (Drosio & Stanek, 2016). The perception of the use of data mining techniques as a strategic management tool in the banking sector from an accounting and financial perspective was also explored (Al Chahadah, El Refae & Qasim, 2018). A co-word analysis framework model has been proposed that encompasses and synthesizes unstructured textual data from web sources to improve decision-making processes to gain and maintain competitive advantage (Sasson, Ravid & Pliskin, 2015).

In the area of health, barriers to DSS adopted by dentists were identified due to their perceived lack of utility, difficulties arising from social and economic factors and in interpreting information from the used systems (Goh, Tao, Zhang & Yong, 2016). In the construction industry sector, it was discussed how the key challenges of data mining from the nature of fragmented data require cultural change and more structured collection systems (Ahmed, Aziz, Tezel & Riaz, 2018).

Data mining techniques using the Bresenham algorithm was used to identify the impact of weather conditions on a given travel route, focusing on fuel cost savings (Lee, Aydin, Choi,

Lekhavat & Irani, 2018). And a combination of flow mining algorithms and online discovery of declaration models, and a model of declarative processes for the transmission of event-producing data was applied in an academic hospital to cancer patients diagnosed by updated images as behavior runtime (Burattin, Cimitile, Maggi & Sperduti, 2015).

The use of data from different sources and in different types is a great challenge for decision-makers. In this research, we can perceive possibilities such as those mentioned above that allow considerable gains for public and private agents in the process of diagnosis and construction of strategies to deal with problems. Thus, when compiling the data in a single system, after collection and treatment, professionals who work with big data can provide inputs for various activities in society.

3.1.6 Big data analytics (BDA) techniques. The health area has been a fertile field for the application of big data (Ashrafi, Kuilboer, Joshi, Ran & Pande, 2014). And the healthcare industry has yet to fully understand the benefits of using BDA (Wang, Kung & Byrd, 2018a). There are still challenges in the adoption of DSS, such as data protection, prejudice and the probability of manipulation in the area of social work (Schneider & Seelmeyer, 2019).

In the governmental field, a paradoxical situation has been identified because on the one hand, we realize the creation of information and knowledge from big data analysis and its use as DSS support in organizations improving the quality and reliability of decisions (Fredriksson, 2018). On the other hand, the monopoly of government control of large amounts of data can have a dangerous influence on citizens for security reasons and/or unreasonable access (Power, 2016).

The use of big data mediated by data diagnosis did not significantly affect the quality of decisions in business studies (Ghasemaghaei & Calic, 2019). However, evidence-based decision-making must address a wide range of issues such as knowledge, belief, social factors and technical capabilities (Power, Cyphert & Roth, 2019). Therefore, we need to understand and present the data source and journey through the right visualization technologies and intuitive platforms for delivering successful messages (Moore, 2017), as the use of unstructured external data challenges companies as to the information accuracy mainly concerning performance measurements (Mello & Martins, 2019).

We highlight the limited availability of tools to provide decision support to improve service management processes (Shrestha, Cater-Steel & Toleman, 2016). However, methodologies and frameworks (Vera-Baquero, Colomo-Palacios, Molloy & Elbattah, 2015), integrated structures of data-driven computational experiments (Long, 2017) and multiagent technologies (Giannakis & Louis, 2016) are proposed to condition scalability and big data processing power. These technologies present themselves as promising alternatives to meet the needs of modern supply chain management at a level of collaboration between organizations and decentralizing operations.

Big Data have been widely applied in logistics, service, planning and manufacturing processes; however, supply chain executives still seem to have a slow adoption in relation to the real potential (Brinch, Stentoft, Jensen & Rajkumar, 2018). Note that when automating business processes, business agility should be considered especially about how the automated process will respond situations where market assumptions may be violated (Groves, Collins, Gini & Ketter, 2014). In general, articles using BDA techniques seek to provide solutions in complex, turbulent environments that often lack a centralized, standardized information collection framework, making it even more difficult for managers to manage data (Osuszek, Stanek & Twardowski, 2016).

3.2 Technologies for big data

The items presented here are related to the application of data analysis technologies to obtain value from big data.

3.2.1 Cloud computing technology. We identified articles that were rated for using cloud computing technology. In order to benefit from the use of big data, companies can instead look for cloud computing for technical flexibility (Boutkhoum, Hanine, Agouti & Tikniouine, 2016); economies of scale, scope and speed in service analysis (Demirkan & Delen, 2013) and further reduce uncertainty and ambiguity in the classification of decision-makers (Boutkhoum, Hanine, Agouti & Tikniouine, 2017). A big data logistics business platform for supply chain network management services has been proposed as a way to modernize logistics services (Neaga, Liu, Xu, Chen & Hao, 2015). In healthcare, an intelligent cloud-based electronic health record system has been developed to improve the privacy and security of electronic records, and it has enabled this application to reduce medical errors and improve patients' quality of life, as well as reducing costs and increasing productivity of health organizations (Khansa, Forcade, Nambari, Parasuraman & Cox, 2012). Finally, the term Climate Analytics-as-a-Service has been presented as a form of business where cloud computing plays an important role as it provides a mobility-driven way of working (Schnase *et al.*, 2017).

3.2.2 Technologies for business intelligence (BI). In our analysis, only two articles were identified with BI technology. The first study highlighted the importance of BI-based decision-making and how its use is critical to ensuring competitiveness and sustainable growth in enterprises (Jin & Kim, 2018). The second presented a prescriptive framework for prioritizing items in business analysis and applying them to the business environment (Pape, 2016).

3.2.3 Technologies for data warehouse. Janković, Mladenović, Mladenović, Vesković & Glavić (2018) present a flexible integration approach from heterogeneous external sources. Big data analysis has enabled integration into big data applications based on batch-oriented processing, as well as flexibility, reuse of raw data and query of various data types and repositories at once. Jukic, Jukic, Sharma, Nestorov & Arnold (2017) describe improvements in tactical decision-making quality that have also been found by providing critical information through analytical databases that combined columnar database technology with an approach based on denormalization of data tables for analysis and decision support. Almeida, Bernardino & Furtado (2015) performed the evaluation of - structured query language (SQL) and no structured query language (NoSQL) scalability platforms, where they concluded that the mechanism was considered more appropriate in transactional systems.

3.2.4 Systems technology. The last group of articles classified in this study was that with those papers that developed or used some information system as a technology application. Baechle, Agarwal & Zhu (2017) described the benefits of improved accuracy of services provided over the short term by applying large dictionaries of chronic obstructive pulmonary disease–related terms. Gillingham (2019b) presents through the principles of algorithmic responsibility, and combination with ethical codes of social work, the possibility for social workers to identify when wrong or biased recommendations are made by the deployed DSS and thereby develop defense strategies for social service users.

Pettit *et al.* (2018) present a tool called planning support system (PSS) used in a study related to smart cities, which assisted in the execution of the main tasks associated with the urban planning process, besides allowing better coordination between the planning and infrastructure agencies of the city, state and the country. Semanjski, Bellens, Gautama & Witlox (2016) demonstrate a case with the applicability of a big data integration approach to the smart city planning process, where the observed benefits were higher data punctuality, shorter cycle time and more informed and agile decision-making for both citizens and city planners. Deal, Pan, Pallathucheril & Fulton (2017) explored the potential of a new generation of conscious PSSs and the challenges of achieving big data.

We can point out from the analysis that as much as DSS are sophisticated tools used to optimize decision-making processes when used in high-pressure and turbulent environments,

they can have negative consequences (Aversa, Cabantous & Haefliger, 2018). Therefore, the use of techniques such as the diffuse analytical hierarchy process (Lan, Zhang, Zhong & Huang, 2016) ends up being a way to optimize the decision-making process in a system.

4. Discussion

Table 3 was structured to answer the first research question of this study. Thus, the application of big data and DSS is applied through techniques and technologies. We can infer that among the identified techniques, the use of BDA was the most, with 16 articles, representing 22% of the sample, followed by supervised classification learning, with 12 articles, which represented 17% of the entire sample analyzed. Regarding technologies, systems had the highest frequency, with seven articles, representing 10% of the sample, followed by cloud computing, with six articles, representing 8% of the sample.

We highlight that the articles in the years 2012 and 2013 used only technologies, and only from 2014, articles using big data analysis techniques were recorded in our sample. We also note that the growth in technology use occurred until 2016, with a decrease in subsequent years. As for the techniques, since the registration of the first article (2014), its use has grown steadily, thus characterizing the increasing applicability of techniques for this purpose. For this finding, we disregard the year 2019 since it was not a complete year for the collection of articles.

Techniques		Articles
Supervised learning	Classification	Hayashi (2016), Rasiulis *et al.* (2016), Rönnqvist *et al.* (2017), Li *et al.* (2017), Ghaddar & Naoum-Sawaya (2018), Nimmagadda *et al.* (2018), Sathiaraj *et al.* (2018), Sivamani *et al.* (2018), Tashkandi *et al.* (2018), Tian *et al.* (2018), Gillingham (2019a), Suh (2019)
Supervised learning	Regression	Ilie-Zudor *et al.* (2015), Ludwig *et al.* (2015), Feuerriegel (2016), Chen *et al.* (2017), Hsu *et al.* (2017), Nguyen *et al.* (2017), Jamshidi *et al.* (2018), Khan *et al.* (2018), Stein *et al.* (2018)
Unsupervised learning	Cluster	Hurter *et al.* (2014), Miah *et al.* (2017), Gao *et al.* (2018), Papagiannidis *et al.* (2018), Giglio *et al.* (2019)
Unsupervised learning	Association	Capobianco & Liò (2015), Chan & Chong (2017)
Semi-supervised learning	Classification	Li *et al.* (2016)
Reinforced learning	Control	Hao *et al.* (2018), Wang *et al.* (2018b)
Data mining		Burattin *et al.* (2015), Sasson *et al.* (2015), Drosio & Stanek (2016), Goh *et al.* (2016), Al Chahadah *et al.* (2018), Ahmed *et al.* (2018), Lee *et al.* (2018)
BDA		Ashrafi *et al.* (2014), Groves *et al.* (2014), Vera-Baquero *et al.* (2015), Giannakis & Louis (2016), Osuszek *et al.* (2016), Power (2016), Shrestha *et al.* (2016), Long (2017), Moore (2017), Brinch *et al.* (2018), Fredriksson (2018), Yichuan Wang *et al.* (2018a), Ghasemaghaei & Calic (2019), Mello & Martins (2019), Power *et al.* (2019), Schneider & Seelmeyer (2019)
Technologies		Articles
Cloud computing		Khansa *et al.* (2012), Demirkan & Delen (2013), Neaga *et al.* (2015), Boutkhoum *et al.* (2016), Boutkhoum *et al.* (2017), Schnase *et al.* (2017)
Business intelligence		Pape (2016), Jin & Kim (2018)
Data warehouse		Almeida *et al.* (2015), Jukic, Jukic, Sharma, Nestorov & KorallusArnold (2017), Janković *et al.* (2018)
Information systems		Lan *et al.* (2016), Semanjski *et al.* (2016), Baechle *et al.* (2017), Deal *et al.* (2017), Pettit *et al.* (2018), Aversa *et al.* (2018), Gillingham (2019b)

Table 3.
Techniques and technologies used in DSS to get value from Big Data

BDA techniques have been widely used as a form of data analysis to interpret past behaviors and relationships. The amount of work using this technique shows us the importance and relevance that BDA has in environments that want to analyze large data sets, mainly for metrics management. Another technique that stood out for the high number of articles in our sample was supervised learning, specifically by classification and regression. Supervised learning techniques seek to define a function that can predict unknown labels from a previously labeled data set.

The low frequency recorded in techniques such as reinforced learning and semi-supervised learning does not necessarily indicate low interest in these applications by researchers. Reinforced learning, for example, has a very fertile field for applications where it is desired to have the least possible decision-making requirement of a person; with this, we understand that they are still new techniques but that have a great potential to be more and more used in our life.

Table 4 was organized to answer the second research question of this study. We note that the issue of scalability in the use of decision systems based on big data is a major challenge. Otherwise, advances make it possible to perceive gains in areas such as healthcare, logistics and supply chain as can be seen in Table 4.

When analyzing the percentage of each field, we noticed that articles directed to the logistics and traffic area had the highest rate, representing 19%; these studies had a predominant focus on the use of algorithms to optimize routes to reduce costs and improve performance. Health, the second group with the most articles (17%), had a predominant focus with studies of disease prediction through diagnoses and support in diagnoses. Business and market also representing 17% of the sample; they presented studies aimed at better decisions for business and social relations. Consideration should also be given to the predominance of studies directed to predictive analysis, that is, an analysis technique that helps to anticipate changes based on understanding patterns and anomalies within data (Hurwitz & Kirsch, 2018).

In line with the findings of Li, Xu, Tang, Wang & Li (2018), we reinforce the relationship between tourism and big data as users are sources of data generation mainly due to devices that allow the collection and interpretation of their movement. In our study, this was evident through the use of social media. We still evidence the impact that big data management has on the market and the business world; Seles, Jabbour, Jabbour, Fiorini, Mohd-Yusoff & Thome (2018) showed the positive effect from an environmental, operational and economic perspective. Convergent also to the study by Rialti, Marzi, Ciappei, & Busso (2019), we highlight the need for big data management in organizations increasingly focused on strategies for decision-making and knowledge management. These data-driven decisions, therefore, are evidence based and stand out when compared to intuition-based decisions (McAfee & Brynjolfsson, 2012).

The verification of the types of problems involved in these applications reflects the capabilities of the professionals involved in this context. The use of big data in DSS, in addition to knowledge in data collection, storage and processing technologies and data analysis techniques, requires professionals to be able to identify specific complex problems, and this requires a profound knowledge of these professionals about these application areas of big data.

We note an inverse relationship in the complexity of the form of data analysis concerning the need for intuition-based human decision-making. For example, Vera-Baquero *et al.* (2015) using descriptive analysis used event correlation mechanisms to monitor instances and processes to assist analysts in their decision-making. Miah *et al.* (2017) through predictive algorithmic analysis identified areas of high photographic activity to find groups at popular tourist sites. And Pape (2016) presented a prescriptive analysis framework for prioritizing items in business analysis and applying them in a business environment.

In this study, the articles had predominance in predictive analysis, thus suggesting an intermediate position of the intensity of complexity in data analysis and the need for human decision-making (Figure 1).

Field	Scope	Articles
Logistic and traffic	Route optimization for cost savings, performance and improvements	Hurter *et al.* (2014), Ilie-Zudor *et al.* (2015), Neaga *et al.* (2015), Lan *et al.* (2016), Chen *et al.* (2017), Hsu *et al.* (2017), Rönnqvist *et al.* (2017), Aversa *et al.* (2018), Hao *et al.* (2018), Jamshidi *et al.* (2018), Jin & Kim (2018), Lee *et al.* (2018), Sathiaraj *et al.* (2018), Wang *et al.* (2018a)
Health	Population health prediction, disease detection assistance and information mapping to improve care	Khansa *et al.* (2012), Ashrafi *et al.* (2014), Burattin *et al.* (2015), Capobianco & Liò (2015), Feuerriegel (2016), Goh *et al.* (2016), Baechle *et al.* (2017), Nguyen *et al.* (2017), Ghaddar & Naoum-Sawaya (2018), Sivamani *et al.* (2018), Tashkandi *et al.* (2018), Wang *et al.* (2018a)
Business and market	Assistance in business decision-making and social relationship improvement	Demirkan & Delen (2013), Boutkhoum *et al.* (2016), Osuszek *et al.* (2016), Pape (2016), Boutkhoum *et al.* (2017), Moore (2017), Ghaddar & Naoum-Sawaya (2018), Janković *et al.* (2018), Tian *et al.* (2018), Ghasemaghaei & Calic (2019), Mello & Martins (2019), Power *et al.* (2019)
Industry and IT	Process efficiency, operating costs and activity optimization	Almeida *et al.* (2015), Sasson *et al.* (2015), Rasiulis *et al.* (2016), Shrestha *et al.* (2016), Jukic *et al.* (2017), Li *et al.* (2017), Ahmed *et al.* (2018), Nimmagadda *et al.* (2018), Stein *et al.* (2018)
Supply chain	Support for strategic decision-making and control of key performance indicators	Groves *et al.* (2014), Vera-Baquero *et al.* (2015), Giannakis & Louis (2016), Long (2017), Brinch *et al.* (2018), Papagiannidis *et al.* (2018)
Weather	Climate analysis to predict retail consumption flow, traffic and crisis management	Ludwig *et al.* (2015), Drosio & Stanek (2016), Schnase *et al.* (2017), Lee *et al.* (2018), Sathiaraj *et al.* (2018), Tian *et al.* (2018)
Tourism and/or social media	Tourist flow trend analysis according to visit log	Li *et al.* (2016), Miah *et al.* (2017), Nguyen *et al.* (2017), Gao *et al.* (2018), Giglio *et al.* (2019)
Financial	Decision support in risk analysis, accounting and stock index trends	Hayashi (2016), Chan & Chong (2017), Al Chahadah *et al.* (2018), Khan *et al.* (2018)
Social problems	Assistance in identifying social problems and mitigating misleading decisions based on the database	Gillingham (2019a), Gillingham (2019b), Suh (2019), Schneider & Seelmeyer (2019)
Smart city	Assistance for planning systems and sustainable urban growth	Semanjski *et al.* (2016), Deal *et al.* (2017), Pettit *et al.* (2018)
Government	Big data collection centralization can give conditions of control over the population	Fredriksson (2018), Power (2016)

Table 4.
Types of issues solved with DSS

We can infer based on the analyzed information that, in the coming years, there should be an increase in the number of works with prescriptive analyzes approaching, given the increase in applications, for example, in studies with autonomous cars and route optimization.

In general, the types of analysis are defined according to the understanding of the problem, so that for data analysis of past events, BDA techniques are used for descriptive analysis, and for inference and prediction problems, in which it seeks to identify possible results and probabilities of an event, machine learning has been used.

Although they have been presented separately, the relationship between the types of problems, techniques and technologies is used to ensure DSS is used as a way to solve

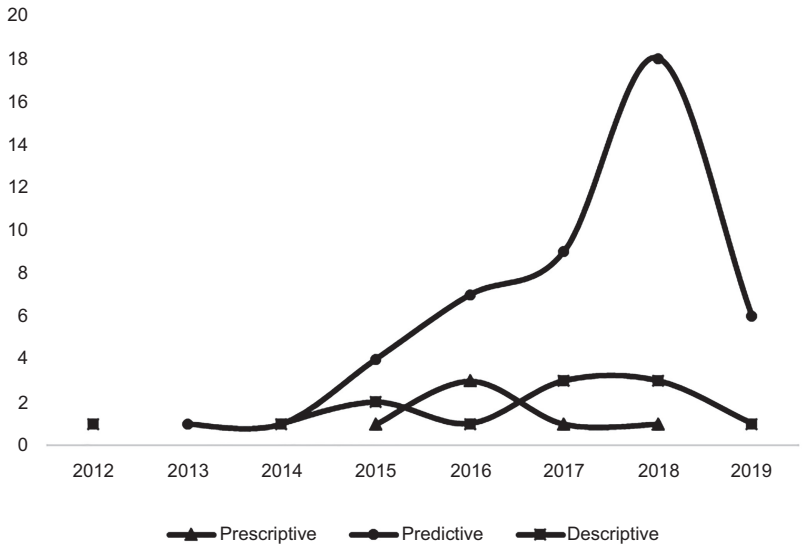

Figure 1.
Types of analysis over time

complex problems, given the human limitation to identify relationships in large data sets. This requires the help of technologies and techniques, which provide mechanisms for obtaining insights that help decision-making.

The value generated by big data in DSS, therefore, occurs when there is better decision-making. For this, techniques and technologies support applications in the most different areas as previously presented. However, the quality of decision-making depends not only on big data but also on the ability to manage the big data chain, from data collection to final insight.

4.1 Research agenda

Analyses of the big data literature have been carried out in some areas; Seles *et al.* (2018), for example, argued that big data management means a major opportunity in corporate sustainability, due to its potential to generate a better understanding of the opportunities and challenges of climate change. Li *et al.* (2018) argued about some disadvantages of using big data in tourism-related situations, due to data quality, data cost and privacy issues. And Bhardwaj, Wodajo, Spano, Neal & Coustasse (2018), when investigating the application of big data analyses in the health area, identified benefits in several phases of the management of chronic diseases and could help to reduce the burden of chronic diseases in patients.

As it is still a new area, research on big data is very recent and, at the same time, there are still many research opportunities to investigate this environment, its challenges and advances obtained over the last few years. With that, we proposed to carry out this comprehensive research, so that it was possible to register areas that the application of big data has been used to solve real problems and also the types of techniques and technologies used more recurrently.

With this, some research opportunities emerge from our results, such as, for example, investigations on the behavioral profile of professionals involved with the development of DSS, which capabilities stand out for certain areas. Another point underexplored and that deserves more attention is related to the ethical issues involved in this type of context, and then it could be researched how ethics is being discussed when developing DSS for decision-

making involving civil control with freedom restrictions, incentive consumption and automatic judgments based on the previous decisions.

Another point that could be explored as an extension to this study would be a research on articles that discuss big data as a source of information for decision-making, without necessarily referring to DSS. The reason for this is that DSS is a terminology that cannot be used by all those who discuss the use of Big Data as a support for decision-making.

5. Concluding remarks

As a result of our study, we note the use of techniques such as BDA, data mining and machine learning algorithms, which were classified into supervised, semi-supervised, unsupervised and reinforcement learning. We also highlight the use of technologies such as BI to report, analyze and present data; cloud computing as a distributed data system provided as a service via the network; data warehouse as a specialized and optimized reporting database, often used to store large amounts of structured data, and information systems. We believe that this is the main contribution to theory.

Through the emerging and incipient subject that the article addresses, we seek to present an overview of the techniques and technologies that are being used to solve problems in their respective areas, as a form of theoretical contribution. This understanding contributes as a way to fill a research gap involving an increasingly important issue for the whole of society.

We have also identified several application areas, such as logistics and traffic for route optimization and operational cost reduction, health for disease detection and treatment guidance, business and market-driven decision-making for competitive advantage and areas with lower application rates in our analyzes as a government in social control and smart cities, in support of urban planning. Within this context of technique or technology applied in some areas, we note the inverse relationship between the complexity of data processing and the need for human decision-making, which results in the form of analysis, which may be descriptive, predictive or prescriptive. In our opinion, this is the main practical contribution of the study.

We also understand that there is a practical contribution to the maturation of the discussion and with reflections even presented as suggestions for future research, such as, for example, the ethical discussion. Our descriptive classification can also serve as a guide for new researchers who seek to understand the research environment involving DSS and big data to obtain value; we believe that this contribution is the most important for society.

We observed that articles related to the theme have increased in number over the years. The ease of access to components that enable data collection and analysis explains the better portability, remote transfer and access of scanned data from one context to another and interconnectivity, the possibility of synthesizing big data and finding connections from the interaction between human and algorithmic intelligence (Günther, Mehrizi, Huysman & Feldberg, 2017), made it possible to improve capturing data and increase the value of big data.

We conclude that the value obtained from big data through DSS occurs with the use of techniques and technologies, which may or not be used together, and that help decision-makers. These insights would not be obtained without using the techniques and technologies in question, given the large volume of data that would make it impossible for a person to collect, store, process and analyze without the aid of DSS.

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About the authors

Gustavo Grander Professional Doctoral Student in Project Management from Nove de Julho University, Master in Business Administration from Western Paraná State University, Specialist in Project Management from Fundação Getúlio Vargas and Production Engineer by the Federal Technological University of Paraná. Has professional experience in the pharmaceutical industry having acted as Project Manager and Project Analyst, metallurgical industry having acted as Production Supervisor and furniture industry having acted as Production Engineer. It has CAPM certification (Certified Associate in Project Management). Gustavo Grander is the corresponding author and can be contacted at: grandergustavo@gmail.com

Luciano Ferreira da Silva Doctorate in Business Administration at Pontifical Catholic University, Master in Business Administration, Communication and Education at São Marcos University, Specialist in Organizational Psychology, Specialist in Human Resources Management and graduated in Business Administration. Professor and researcher at the Graduate Program in Project Management at Nove de Julho University. Experience in organizations in market assessment, sales projection, survey of new business opportunities and training. Author of the book "Legal Revolutions - Brazilian law and politics", as well as other academic works in the area of operations, sustainability, People Management, Project Management, among others. Scientific Editor at "Gestão e Projetos" magazine.

Ernesto Del Rosário Santibañez Gonzalez Associate Professor in the Department of Industrial Engineering, Executive Director and Founding Council of Industry-University – Talca University. He is associate editor of the *Journal of Cleaner Production* and *Journal of Intelligent Manufacturing*, on the Editorial Board of the *Journal of Power Sources* and the *International Journal of Hydrogen Energy* and is a guest editor of six special editions of ISI and Scopus journals, including the *International Journal of Research, Sustainability*, *European Journal of Operational Research*, *Clean Production Journal*, and Guest Editor for two special editions of ISI journals, including the *International Journal of Production Economics*, *Computers and Industrial Engineering*.

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