A BIG DATA-ORIENTED APPROACH TO DECISION-MAKING: A SYSTEMATIC LITERATURE REVIEW

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Abstract

The advent of ICTs and Big Data led to the redefinition of decision-making to interpret big data analysis as a key corporate asset. Thus, the work aims at assessing the main strategic and operational levers enabled by big data to enhance decision-making effectiveness.

The study employs PRISMA methodology to conduct a systematic literature review on academic articles extracted from various databases to identify trends in extant research on big data and decision-making.

Two major drivers for an effective use of big data in decision-making are identified: 1) the strategic reinterpretation of business orientation according to a culture of data as a strategic asset; 2) the identification of the most adequate skills, analytics and resources to implement big data-oriented business models at an operational level.

The work can help academics and practitioners understanding the main levers to attain competitive advantage through the adoption of Big Data in all the phases of business processes. The classification of the main enabling factors of Big Data orientation to decision-making can foster the introduction of a strategic view to understand how big data can reshape organizational processes.

Keywords
Systematic literature review; PRISMA; Big Data; Big Data Analysis; Big Data Analytics; Decision-Making.

1. Introduction

The increasing complexity of contemporary markets implies the need to develop effective and timely decision-making processes as a core strategic capability of firms (Gonzáles and Kasper, 1999). The advent of ICTs and big data can provide decision-makers with the possibility to gain a great amount of information and to select the most proper business decisions more rapidly.

The impact of big data on management effectiveness is acknowledged in literature (Chen et al, 2012; Ferraris et al., 2018). In particular, extant research focuses on the key role of data extraction and of the subsequent generation of useful information and knowledge, interpretation and categorization on the attainment of competitive advantage (Davenport, 2013).

Even if good data can lead to good decisions, the high volume of the data collected from multiple external and internal sources can exceed the capacity of storage and analysis tools. Thus, to exploit the advantages deriving from Big Data analysis and from the use of Big Data analytics, there is the need to understand how data can be managed to improve decisions (Provost and Fawcett, 2013; Zhou et al., 2014). The quality of big data, in fact, does not derive only from data per se but from the adequacy of data collection and processing. The useful interpretation of big data to enhance business process requires often the integration of different skills owned and shared between and among different actors thanks to the accomplishment of diverse practices to examine the underexplored relationships between data (Russom, 2011; Janssen and Kuk, 2016). Therefore, to extract relevant information from big data, managers and employees (from IT to R&D and marketing departments) should combine different capabilities. Since the main objective of the process of examining massive amounts of data is to uncover hidden patterns, unknown correlations and other useful information (Shanmuganathan, 2014; Wuet al., 2014), to reach this goal, organizations should develop actionable insights and new knowledge.

Hence, big data analytics can be considered as a key component of decision-making processes in different kinds of businesses due to a new proactive and forward-looking approach (Hagel, 2015).

For this reason, the role of big data in decision-making process and the key levers to enhance decisions effectiveness thanks to the use of analytics should be explored.

Therefore, due to the recognized need to explore deeply a complex topic such as big data and its influence on firm's decision-making and its main drivers (such as actors, technologies, resources), the work proposes a systematic literature review aimed at addressing the following research questions:

RQ1: Which are the main strategic approaches to big data and the key levers that can foster the use of big data for decision-making effectiveness?

RQ2: Which are, at an operational level, the main drivers to implement big data effectively in decision-making process?

The research questions are addressed through a systematic literature review on the role of Big Data in decision-making. The reminder of the paper is organized as follows. In the next section, a brief overview on Big Data in decision-making is proposed. Then, the methodology used in literature review, based on the *Preferred Reporting Items for Systematic review and Meta-Analyses* (PRISMA, Moher et al., 2009) model, is presented. In the following sections, the result of the systematic literature review are reported and discussed by identifying: 1) the key elements involved in the potential adoption of a strategic approach to big data; 2) the main analytics that can be adopted to redesign business processes through big data. Finally, implications, conclusion and limitations of the work are debated.

2. Defining the issue: the role of big data in business decision-making

The recognized impact of Big Data on the redefinition of business strategies leads extant research to focus on the analysis of how Big Data can reframe decision-making.

"Big data" refers to the collection and analysis of "large" data sets. The concept is defined according to five integrated criteria, the five "V" (volume, velocity, variety, veracity, value), identified by Laney (2001) and then revised by Diebold (2012) and Song and Zhu (2015). Volume refers to the huge quantity of data produced by companies; velocity refers to the speed of data creation, production or renovation; variety concerns the diversity of data types and data sources (Fosso Wamba et al., 2015; White, 2012); veracity is related to reliability of data source (Chern et al., 2015; Sun et al., 2015); last, value is the meaningfulness of data collected to pursue business goals.

However, the relationship between decision-making and data analysis is not new in literature. In the interpretation of strategic decision-making as a process of making choices under varying conditions of uncertainty (Milliken, 1987; Petrakis et al., 2016), previous literature identifies the lack of information, and of the proper interpretation of this information, as a key source of uncertainty (Nutt and Wilson, 2010). In big data era, technological evolution transformed the lack of information into abundance, or even into a real overload, with the potential to reshape data into usable information (Tihanyi et al., 2014) but also to increase chaos, to prevent the selection of relevant information from multiple sources and to foster "involuntary" data collection.

In fact, when individuals make decisions, the process is often biased or limited by humans' inability to process a great amount of information. Thus, the capacity of firms to manage, analyze and interpret big data (Wamba et al., 2017) is one of the most relevant topic explored in literature. Thus, managers can use big data to raise the knowledge about their businesses and transform the knowledge generated by improving performance and the entire decision-making process (Gupta and George, 2016).

Some emerging streams of research, by highlighting the positive effects of big data analytics within organizations, focus on the potential improvement of strategic decision-making thanks to the adoption of a more holistic view of leadership (Filatotchev and Nakajima, 2010). Additionally, further economic and social value can gained from big data through enhanced decision making (Sharma et al., 2014) and more informed strategizing (Constantiou and Kallinikos, 2015).

Over the course of time, the relevance of human component and the ability to extract significant insights from data led to the reinterpretation of big data as a strategic asset that should encourage organizational members (at each level) to make decisions based on the knowledge extracted and to foster decisions' effectiveness (LaValle et al, 2011; Provost and Fawcett, 2013). Moreover, the need to integrate data extraction and management with the following interpretation of information thanks to creativity is emphasized in the proposition of a learning- based perspective (Chen et al., 2016).

Therefore, due to the increasing need to consider big data as a strategic approach toward the reinterpretation of business orientation that considers data as a strategic asset, the following research question can be introduced:

RQ1: Which are the main strategic approaches to Big data and the key levers that can foster the use of big data for decision-making effectiveness?

Together with a strategic orientation to data, Big Data and Big data analytics should be adopted in business models to build an integrated ICTs-based and technology-based infrastructure.

One of the most powerful aspects of the big data revolution is the unification of large data sets with advanced analytics for problem solving. The ability to solve problems beyond human mental capabilities has led to two main sources of insight derived from big data. First, very large and multidimensional data sets can be examined to look for previously hidden patterns and correlations. Second, big data opens up the realm of reliable predictive analytics. By examining the relationships embedded in large data sets, it is possible to build a new generation of models describing how things are likely to evolve in the future (Ferraris et al., 2018).

A synergistic approach to the implementation of a coherent set of technological instruments can help managing the huge amount of data across the different data points and sources, by breaking down information asymmetries and gaining relevant information in real time. For instance, the combination of sensors, mobile applications and internet of things can contribute to establish an effective and efficient urban infrastructure to simplify the provision of public services and to increase the economic social and technological development of community.

As the sources of data grow richer and more diverse, a series of organizational components and resources should be used to extract useful insights and to make decisions faster, more accurate and transparent. There are many examples of how this can play out in industries and domains across the economy.

Hence, big data and big data analytics should be integrated in technology-based business model to exploit the advanced possibility to store, manage and analyze data (Chen et al., 2012) as well as to perform sophisticated statistical analysis. At an operational level, the impact of big data can result in more efficient operations, in the development of innovative products and business opportunities (Davenport et al., 2012; Davenport and Kudyba, 2016), in the optimization of supply chain (Chen et al., 2012; Davenport, 2006; McAfee and Brynjolfsson, 2012).

In this way, the impact of big data analytics on the enhancement of the main drivers to improve competitiveness and growth can be observed in order to reveal and categorize the main drivers and tools of an effective big data integrated architecture (Blazquez and Domenech, 2018). Thus, the following research question is introduced:

RQ2: Which are, at an operational level, the main drivers to implement big data effectively in decision-making process?

3. Methodology

3.1 Research approach

To analyze the key (strategic and operational) role of big data in business decision-making a systematic literature review based on qualitative content analysis is performed.

The main objectives of the research are: 1) to assess the (potential) existence of different strategic approaches to Big Data and to detect some main strategic levers for improved decision-making; 3) to explore the main drivers (big data analytics, resources, etc.) that can translate the strategic orientation to data into the creation of an integrated technological architecture.

Therefore, the review is conducted by mediating between two different viewpoints:

- Strategic-macro perspective: that reveals the key levers identified in extant research of a strategic orientation to data aimed at exploiting and extracting relevant knowledge from data to improve decision-making;
- Operational-perspective: that detects the main operational drivers proposed in previous literature as enablers for the exploitation of the possibilities offered from big data and for the successful utilization of an integrated technological architecture.

The literature review has been conducted between February and May 2019 by three researchers from the University of Salerno according to PRISMA (*Preferred Reporting Items for Systematic Reviews and Meta-Analysis*) methodology (Moher et al., 2009).

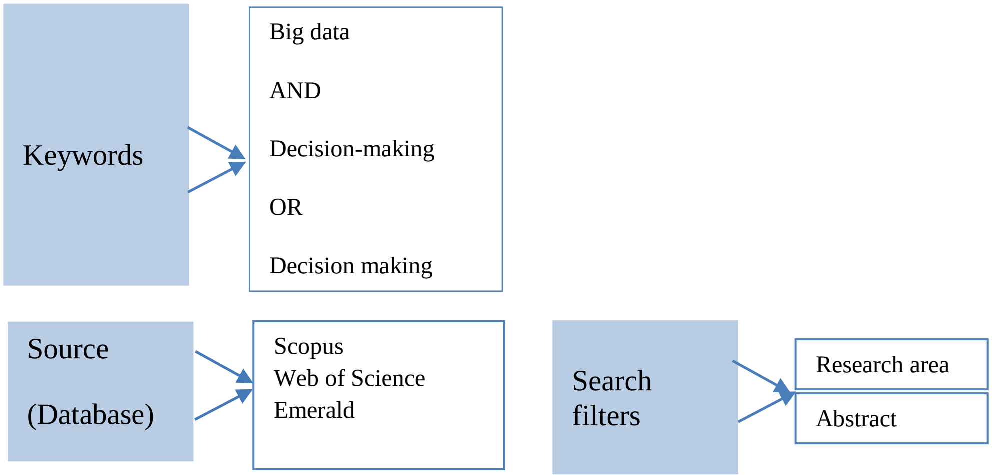
This approach allows at conducting an in-depth investigation of a huge number of contributions to shed light unexplored issues and to derive unexpected results (Mulrow, 1994). Moreover, thanks to a four-steps and a well-defined process, PRISMA offers methodological accuracy replicability and transparency (Tranfield et al., 2003).

3.2 Describing the review process

3.2.1 Data collection

To obtain an adequate coverage of the issue, three databases have been used according to their extensiveness and relevance in social sciences: 1) Scopus; 2) Web of Science; 3) Emerald. A filter based on temporal criterion has been applied to the search engines: only the works published between 2009 and 2019 have been included in the analysis. The selected keywords have been connected with the "AND" and "OR" Boolean operators. Thus, the following search string has been defined: "decision making" "OR" "decision-making" "AND" "big data".

Figure 1. The process of data collection



Source: author’s elaboration

3.2.2 Data extraction procedure and inclusion criteria

The four phases performed according to the PRISMA framework (see Fig. 1) are: 1) identification, 2) screening, 3) eligibility, and 4) inclusion.

After having matched the results obtained from the three databases during the identification phase (7994 from Scopus, 3749 from Web of Science, 880 from Emerald), drawing on the two research questions some research filters have been applied to eliminate 6776 papers. Duplicates (451) were removed and 767 studies were screened around according to their titles and abstracts in order to exclude the less relevant contributions (278) (*screening phase*).

Then, based on the reading of 489 abstract, 438 papers were deleted, because of their low pertinence to research aims (*eligibility phase*). By borrowing from Cooper’s methodology (1998; 2010), the final criteria used to select the eligible studies were:

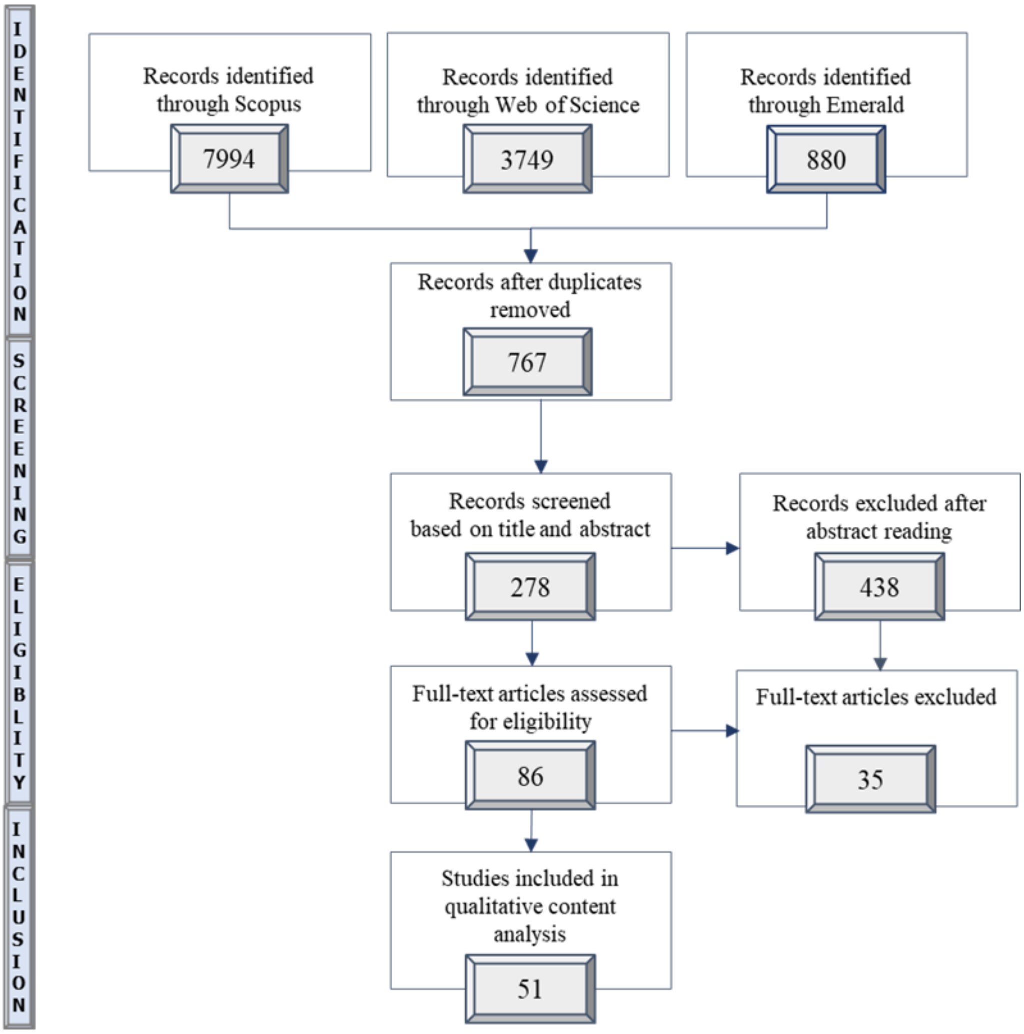
- he appropriateness of the research area (management, business management, decision science, social sciences, information and knowledge management) based on the classification of the given database;

-the kind of publication: conference proceedings, editorials or working papers have been removed to include only full papers and literature reviews;

-the language of the article (english).

Finally, according to the application of eligibility criteria, a final set of 51 works (inclusion phase) was analysed.

Figure 2. The assessment and selection of contributions: PRISMA flow diagram



Source: author's elaboration

Then, an inductive methodology, based on the content analysis (Kassarjian, 1977; Graneheim and Lundman, 2004; Krippendorff and Bock, 2009) as applied to the final set of works resulting from the systematic literature review. No a priori classification criteria were used to analyse the selected papers, while in the sampling phase specific keywords were used to simplify the screening of the several contributions resulting from the initial research stages.

3.2.3 Data Analysis

Content analysis has been selected as an adequate technique to examine deeply the key semantic shades of meaning of the topic analyzed to address the research questions.

Content analysis is employed commonly in research to make replicable and valid inferences from texts (or other meaningful matter) in the contexts of their use. Thus, it can be helpful to derive relevant knowledge from a large amount of texts using both qualitative and quantitative approaches (Krippendorff, 2012).

In exploratory research, content analysis seems to be a proper technique, based on researcher's subjective interpretation and critical attitude, to inspect deeply (from a conceptual and semantic viewpoint) constructs that are not conceptualized well in literature.

Qualitative content analysis is defined in literature as "inquiry content analysis" (Rositi, 1988; Losito, 1996). This technique extracts from texts (the unit of analysis) fewer content categories in a non-automatized way and reveals the focal points of the studies (Krippendorf, 2004) through the adoption of semantical criteria established by the researcher. The unit of analysis is not a sample of individuals but an entire text (stories, articles, papers, advertisements, etc.) and the pen-and-paper survey is replaced with an analysis sheet in which researchers trace the absence or presence of some main elements established a priori thanks to their subjective knowledge and research aims (see Appendix A).

Content analysis as inquiry implies also the investigation of semantic elements, such as values or in general author's standpoint or attitude toward a given issue which can be deduced by researchers thanks to their personal knowledge about the research field. For this reason, this technique seems to be the most adequate to meet the research aims and in particular RQ1 that pertains to the identification of the potential existence of a strategic view on big data that can foster the effectiveness of decision-making. The investigation of orientations or approaches to the issue of Big Data requires a careful interpretation of researchers based on his/her personal experience, knowledge and critical and analytical thinking.

4. Findings

4.1 Description of the sample

Concerning the journals on which the 51 works are published, as Table 1 shows, management journals in general outnumber computer science journals. In detail, knowledge management and business process management are the most common research areas in the sample, by showing the relationship between the analysis of Big Data and its implications on both strategic management and operations. Thus, the results from the selection process are in line with the research questions by producing a final set of works pertinent to the aims of the study.

However, the fact that the sample is balanced between contributions deriving from knowledge management and information management guarantees a certain representativeness, even if the exploratory work does not provide generalizable results.

Moreover, this finding complies with the purposes of the review and shows the appropriateness of the eligibility criteria adopted and of the strategy employed to exclude too broader studies in order to address specific research aims.

Table 1. The final list of articles analyzed sorted by journals

Journal	Frequency
Journal of Knowledge Management	7
Journal of Business Research	4
Journal of Decision Systems	3
Management Decision	3
Harvard business review	3
International Journal of Information Management	3
International Journal of Computer Information Systems and Industrial Management Applications	2
International Journal of Logistics Management	2
Lecture Notes in Business Information Processing	1
Journal of systems science and systems engineering	1
Profesional de la Informacion	1
Interdisciplinary Journal of Information, Knowledge, and Management	1
Technological Forecasting and Social Change	1
IEEE Potentials	1
Journal of Computer Information Systems	1
Information Processing and Management	1
Data and Knowledge Engineering	1
Decision Support Systems	1
Operations and Supply Chain Management	1
International Journal of Digital Accounting Research	1
Big data Research	1
Business Process Management Journal	1
International Journal of Operations and Production Management	1
Business Horizons	1
International Journal of Digital Television	1
Intelligent Systems in Accounting, Finance and Management	1
Economics of Innovation and New Technology	1
Sustainability	1
Information Technology & People	1
Journal of Enterprise Information Management	1
International Journal of Production Economics	1
International journal of information systems and project management	1

Source: author’s elaboration

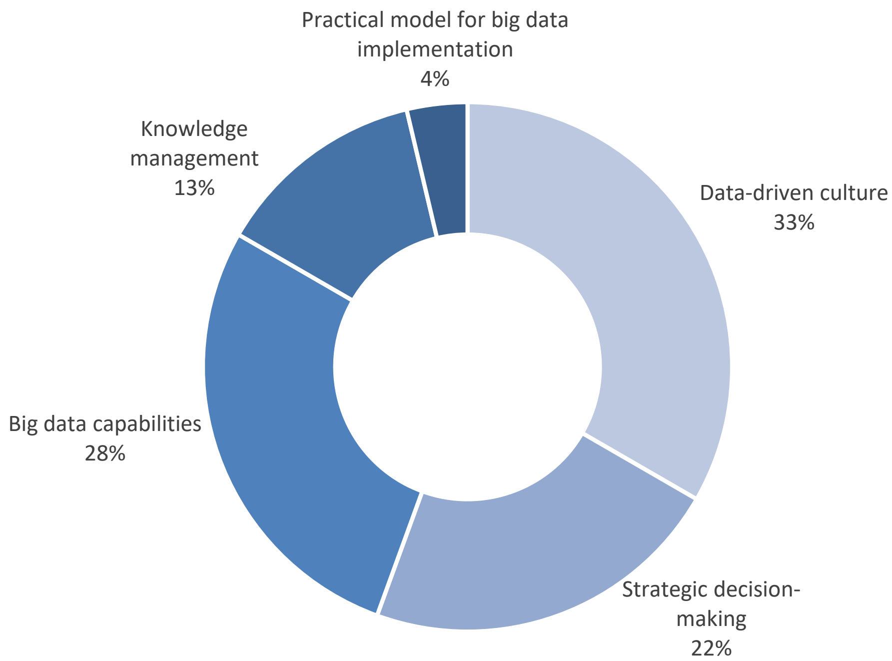
Moreover, regarding the main research streams from which the contributions derive (see figure 3), it can be noticed that, in line with the most common journals in the sample, knowledge management and strategic decision-making are the leading research fields.

In detail, with reference to RQ1, three main research areas have been detected: 1) strategic decision-making (22%): contributions on the integration of Big data into business strategies and decisions; 2) data-driven approach (33%): works adopting the specific conceptual framework of data-driven decision- making (DDDM); 3) knowledge management (13%): articles proposing a strategic view on Big data centred on the relevance of the proper selection of skills and resources in line with a data orientation.

To address RQ2, a series of works that explore the different resources and skills that big data-oriented organizations should acquire to implement data-oriented business models are analysed. Two maim macro-areas can be identified: 1) big data capabilities (28%): works that classify the proper skills, technologies and resources that firms should own to benefit from the advantaged of big data; 2) practical models (4%): contributions that reveal the different drivers to implement an integrated technological architecture based on data-driven approach.

Therefore, to confirm the relevance of the strategic approach to Big Data, the majority of works (74%) stems from the area of strategic management whereas the remaining 26% refers to the operational level. The classification of works into main macro-areas can be intended as a first result that confirms the need to adopt strategic data culture for decision-making (RQ1) and to assess the key drivers and resources for the realization of technological architectures and business models that integrate big data analysis and analytics into business process.

Figure 3. The final list of contributions sorted by research stream



Source: author's elaboration

4.2 Content analysis: results

Data analysis is based on the identification of some preliminary keywords deriving from a semantic specification of the main topics related to the objectives of the study and elaborated according to author's extant knowledge. Then, the researchers detected the presence of these sub-dimensions in the works analyzed to shed light on the points of contact and on the differences between the contributions in the sample. As table 2 shows, these main keywords have been detected for each research question.

Table 2. The main keywords employed for coding based on RQs and on the two level of analysis

Macro- strategic level	Micro- operational
RQ1- Main strategic approach(es) to Big Data for decision-making	**RQ2- Operational levers for the implementation of a big data**
Strategic	Innovation
Culture	Operational/Operations
Decision	Tactics
Strategic management	Process
Knowledge	Resources
Strategic Decision-making	ICTs
Human	Architecture
Leadership	Platforms/ Tools
Learning	Mobile
Information management	Data mining
Attitude	Social media
Big-data oriented	Applications
Orientation	Big data analytics
Value	Performance
Fit alignment	Efficacy/Effectiveness

Source: author's elaboration

The final classification has been obtained through a process of substruction (Dulock *et al.*, 1991; Bekhet and Zauszniewski, 2008), a strategy that identifies the main variables in a study, their levels of abstraction and the logical relationships among them according to a hierarchical model that moves from the abstract to the concrete, by relating key concepts, propositions, and operationalization.

The initial set of keywords –employed as guidelines to orient the first reading of the contributions- has been reelaborated continuously in progress in order to adapt to the results emerging while performing the process (see Appendix B). Thus, extant knowledge has been enriched constantly and incrementally based on the new knowledge arising in progress during the analysis and based on the comparison with the other works in order to search some commonalities and differences.

Some macro-areas have been confirmed, whereas others have been specified further or even disappeared or have been simplified. The works have been coded from three researchers independently; during the process, the labels identified before the coding were revised and then- after the combination of the results obtained from the three researchers- were matched in order to be employed as the starting point for the interpretation of findings.

4.2.1 RQ 1: strategic orientation to big data for decision-making

The findings for the first research questions derive from the analysis of the contributions that introduce the need to adopt a strategic orientation to the integration of Big Data in business decision-making. Three main research areas have been identified: 1) strategic decision-making; 2) data-driven culture; 3) knowledge management. For each research area, some strategic levers for the proper realization of data-oriented organizations are detected.

The first research area (*strategic decision-making*) refers to the studies that propose to reframe the traditional process of decision-making through the different phases of big data analysis: from data collection to information extraction and generation of new knowledge at the end (Xu et al., 2016).

According to this perspective, an effective use of big data analysis and analytics should be attained only through the elaboration of explicit strategies to guide analytic activities and through the design of proper structure and process to enable the application of technological tools (Fan et al., 2015). The strategic integration of big data into business process can give birth to the reinterpretation of decision-making cycle thanks to the different steps of big data analysis, through the fulfillment of the following phases: data generation, data acquisition, data storage, advanced data analytics, data visualization and decision-making for value creation (Saggi and Jain, 2018).

The key lever to perform the strategic integration of big data into business processes (according to the studies in the sample) is top management support, considered an organizational factor affecting the effectiveness of the process decision's adoption. Managers should own the full control of the organization to support the use of analytics in line with strategic objectives and to encourage and promote analytics-driven decision-making based on the information and insights provided by platforms. Through a supportive attitude, managers can establish an analytics-driven culture by empowering business users to explore data and generate actionable insights that they can employ readily to improve business planning, processes, and customer engagement (Daradkeh, 2019).

The second research area (*data-driven culture*) is composed of all the works that adopt and comply with *data-driven decision-making* (DDDM, LaValle et al., 2011; Brynjolfsson et al., 2011). Data-driven is a mind-set that conceives data as strategic resources and that propose data, rather than intuition and experience, as a basis for decisions.

This approach requires the active role of leadership in fostering an innovation-oriented culture and the careful attention to data management in each step of decision-making. In fact, literature emphasizes the need to integrate data extraction and management with the following interpretation of information thanks to creativity (Provost and Fawcett, 2013). Data-driven managers should base business decisions on data-analytic thinking in order to use the data collected as a driving force to prescribe actions, predict complexity and "make" the change.

Inculcating a data-driven mindset should be a key thrust area for the top management since the culture of basing decisions on data instead of hunches and intuition is a challenging task (Wielki, 2013). Therefore, management attitude and the adoption of a proactive innovation mind-set can foster the effectiveness of decision-making based on data analytics.

Key organizational decision makers play a central role in the success or failure of big data initiatives and are responsible for creating a unified vision regarding the approach to big data analytics in organizations (Rasmussen and Ulrich, 2015). They can create and sustain a data-driven culture that values evidence-based decision making and encourages transformation of data into insights, insights into decisions, and decisions into successful execution. Thus, the applications of advanced technologies and analytics does not imply the automatic attainment of competitive advantage. As Gupta and George (2016, p. 5) highlight: "intelligence gleaned from data will be of little use to an organization if its managers fail to foresee the potential of newly extracted insights"

Therefore, in the light of the relevance of human and managerial dimension, the main strategic levers of DDDM for the integration of big data into decision-making are: 1) managerial commitment; 2) change management.

Managerial commitment to big data projects contributes to the generation of a data-driven culture by sending the right signals to everyone in the organization (Adrian et al., 2018). The active engagement of managers that spread throughout the organization a culture based on data can enhance employee's motivation and can enhance the activities of talent acquisition, data acquisition and data management systems by addressing firm's technological needs. Overall, managerial commitment can significantly mitigate the cultural and technological barriers to big data strategies.

Change management focuses on engaging the various stakeholders, evaluating the organization's readiness in case of change in business environment, facilitation of training and learning needs of employees and controls the change process. The idea behind change management process is to focus on short-term wins in initial phases, report the benefits derived and building on incremental successes to push data-driven decision making into the culture of the organization (Lamba and Sing 2018). Change management is critical to the success of big data. It has been predicted by Gartner Inc., a leading research and advisory firm, that through 2017, around 60 percent of big data projects will not go beyond piloting and experimentation stage and will eventually, be neglected due to lack of change in mindset and organizational culture). In order to make big data initiatives successful, it is imperative that the people who understand the problem, who also usually happen to be the decision makers, work with the right people, right data and right problem solving techniques.

Thus, manager's proactive search for data that should be turned into market information and, throughout subsequent interpretation, into the most proper marketing decisions (Atuahene-Gima and Li, 2004; Atuahene-Gima and Murray, 2004)

Lastly, in the third research area (*knowledge management*) some contributions that affirm that effective decision-making can be attained through the use of knowledge generated from big data analytics can be identified (Murdoch and Detsky, 2003). Chen et al. (2014) argue that enterprises can use big data analytics to generate knowledge to improve competitiveness and to generate benefits for the whole value chain: from the prediction of consumer behavior, to the optimization of prices and the simplification of logistics. To manage better the extracted knowledge and increase value, there is also a strong need for forward-thinking companies to build Big Data analytics capabilities.

Big data analytics help in understanding and extracting valuable knowledge from the huge volumes of data, and this knowledge then can be used for enhancing the performance of many different processes in an organization (Sumbal et al., 2017). This links big data to KM capability as well because of its potential for valuable knowledge generation and the ability to improve the organizational processes. Therefore, a relationship can be seen as to how knowledge can be created through big data and further used for enhancing organizational performance.

Thus, according to Teece et al. (1997), usage of big data can be termed as reconfiguration capability of organizations to determine the capacity to absorb untapped knowledge in big data and deduce generalizable cause effect relationships with existing knowledge for improved performance. Another goal of knowledge management is to integrate and analyze the information from different perspectives for valuable decision-making Lamont, 2012). Similarly, organizations also want data to be consistent and in an integrated form because then it is easier to extract knowledge from it (LaValle et al., 2013).

The willingness to turn the data collected into information and, then, into a knowledge flow that surrounds business process leads to the introduction of the concept of data-driven environment.

To exploit the opportunities offered from big data, an organization should change its environment to reframe process and create a data-driven environment to know on "which data to focus, how to allocate analytic resources, or what it is trying to accomplish in a data-to-knowledge initiative (Davenport et al., 2001, p. 122).

The three macro-areas and the main strategic levers identified are synthesized in table 3.

Table 3. The main findings of the analysis related to research question 1

	Key research streams	**Key topics**	**Strategic levers**	**Authors**
RQ1- *Strategic orientation to Big Data for decision-making and key strategic levers for effective decision-making*	**Strategic- decision making**	Integration of big data analysis (collection, extraction, integration, interpretation) into business strategies (objectives, selection of resources, creation of value) Redefinition of business decision-making through management's supportive and empowering attitude	*Top management support*	Bertei et al. (2015); Fan et al. (2015); He et al. (2017); Intezari and Gressel (2017); Izhar et al. (2017); Storey and Song (2017); Brinch (2018); Brinch et al. (2018); Fosso Wamba (2018); Fredriksson (2018); Izhar et al. (2018); Jeble et al. (2018); Saggi and Jain (2018); Sun et al. (2018)
	Data-driven culture	Business orientation based on data as key strategic asset for effective decision-making Big data and analytics do not imply the attainment of competitive advantage Relevance of : 1) human dimension: 2) proactive and innovation-oriented mindset	*Managerial commitment* *Change management*	McAfee and Brynjolfsson (2012); Davenport (2013); Ross et al. (2013); Phillips-Wren and Hoskisso (2015); Ylijoki and Porras (2016) Frisk and Bannister (2017); Janssen et al. (2017); Sivarajah et al. (2017); Tian (2017); Acharya et al. (2018); Roßmann et al. (2018); Akter et al. (2019); Daradkeh (2019); Niebel et al. (2019); Pugna et al. (2019); Tabesh et al. (2019)
	Knowledge Management	Knowledge extraction from data as a key asset for competitiveness in the entire value chain Capabilities and skills as enabling factors for big data analysis Synthesis and harmonization of knowledge flows for the creation of a data-driven environment	*Data-driven environment*	Cao and Duan (2017); Pauleen et al. (2017); Sumbal et al. (2017); Ferraris et al. (2018).

Source: author's elaboration

4.2.2 RQ2: key drivers for the implementation of big data architecture

After the assessment of a strategic orientation to big data adoption, the second research question aims at detecting the key levers needed to translate this approach into the implementation of integrated big data architecture and of data-oriented business models. In fact, the real utilization of big data analytics and all the insights deriving from the data collected should be linked closely to business strategy and embedded into organizational processes. By connecting the use of analytics with strategic goals, organizations can perform the right action at the right time (Balboni and Cook, 2012).

Hence, the results for the second research question (synthesized in table 4) allow at detecting two main research streams that reveal the existence of two main operational drivers for big data: 1) BDA capabilities: that explores the right skills to manage big data as a driver for decision-making effectiveness; 2) practical models to use big data analytics: that propose the combination of different analytics to build an integrated architecture.

The first research stream (*big data analytics capabilities*) is composed of contributions that, in line with the consideration of big data as strategic asset (Gupta and George, 2016), argue that competitive advantage may be created and sustained not only thanks to the "simple" adoption of analytics but through the building and combination of capabilities related to the use of big data. Firms need to adopt integrated bundle of resources in order to create unique capabilities, difficult to be imitated and that can foster the attainment of greater performances and distinctiveness.

A wide range of skills is needed to use big data that can be classified into two main areas: 1) hard skills: technical, analytical and managerial skills; 2) soft skills: communication, interactional and creative skills.

Big data-oriented organizations need, on the one hand, to acquire new competencies and talents and, on the other hand, to enrich and develop the extant knowledge of employees.

New and "old" employees should own a differentiated set of skills that can range from technical, analytical and governance skills to relational skills (Davenport et al. 2012; Kiron et al. 2014; Schroeck et al. 2012). The main "hard" skills identified from literature are:

- *technical*: good knowledge and capabilities to deal with big data and analytics (software, language programming, databases, cloud systems) and to extract relevant information from analysis;
- *analytical and methodological skills*: to interpret the analysis in line with strategic objectives to identify solutions for service/product or performance improvement;
- *organizational skills*: coordination of data-driven decision making processes at all levels of organization to make employees in the different departments internalize overall strategic objectives and align data analysis with the business goal.

As argued by McAfee and Brynjolfsson (2012) and Kiron et al. (2014), after having collected the enormous amount of big data, this should be selected and analyzed through technical and analytical skills o (cognitive, methodological and statistical skills). Moreover, to promote cross-functional collaboration in the implementation of big data analytics strategies, the importance of building multi-skilled teams and manage them properly has been emphasized. Thus, managers should own the general knowledge on data analytics and should integrate them effectively into decision processes (Zettelmeyer, 2015).

Soft skills seem not to affect directly big data analysis but can be considered as critical factors for the effectiveness of data interpretation and extraction of knowledge. Three kind of soft skills can be revealed:

- *creative skills*: the ability to turn data into information that can be transformed into knowledge to develop learning and creativity in a circular process of constant improvement. Data interpretation should consist in the extraction of knowledge and innovative insights from information synthesis to develop new strategies, new service development and potential innovation;

- *communication skills*: ability to explain the analytical results collected from big data analysis to streamline business process and facilitate communication (Aiken and Gorman, 2013). The establishment of multiskilled team facilitates the communication in real time of data and results between managers and technical staff and can help managers transforming them into business decisions (Mayhew et al., 2016) ;
- *interactional skills*: ability to relate, cooperate and communicate with internal and external parties (Thirathon et al., 2018) by understanding the needs of internal customers, collaborating and contributing to team results, negotiating and conflict resolution and effectively communicating problems and solutions.

The second research stream (*practical models to use big data*) consists of works introducing some practical models to conceptualize the key operational drivers for the implementation of an integrated big data architecture.

According to these contributions, big data-oriented organizations should select and combine harmonically the most appropriate big data technologies and techniques to create a technology-driven ecosystem (Saggi and Jain, 2018; Barile et al., 2017), where the extraction of knowledge in an interpretable and appropriate form can improve decision-making.

The main tools of this integrated technological infrastructure (according to the works included in the sample) for big data analysis are:

- *Internet of things*: combination of connected physical and mobile devices for the development and deployment of information systems that integrate data collection, integration and information dissemination (Brous et al., 2019 ; Jonoski et al., 2010) between and among different ecosystems (from smart cities to smart helthcare, etc.);
- *Storage systems*: cloud computing and relational or non relational databases (SQL or NoSQL) that allow at store useful information (users' data, purchase orders, reviews) to extract relevant knowledge for the improvement of quality and relationship with users (Storey and Song, 2017 Lamba e Singh, 2018);
- *Machine learning techniques*: predictive analytics, data mining and other techniques that require statistical learning and network science to convert data resources into actionable knowledge (Suthaharan, 2014; Archetti et al., 2015);
- *Cognitive computing systems*: machine learning systems that enable decision-making thanks to circular learning mechanisms and allows machines to communicate with operators in natural language. Some specific techniques such as decision support systems (DSS), scenario and fuzzy logic support human decision-making and guide problem solving by detecting alternative courses of action starting from data (Chen et al., 2016).

Table 4. The main findings of the analysis related to research question 2

	Key research streams	Operational drivers	Key topics	Authors
RQ2- *Operational drivers to implement big data in decision-making process*	**BDA capabilities**	*Hard skills* -Technical -Methodological -Organizational *Soft Skills* - Creative - Communication - Interactional	Identification of a wide range of skills needed to use big data Need to acquire new competencies and talents and to enrich and develop the knowledge of employees	Power (2013); Dutta and Bose (2015); Phillips-Wren and Hoskisson (2015); Fernández-Manzano et al. (2016); Uden and He (2017); Moore (2017); Sivarajah et al. (2017); Tian (2017); Ferraris et al. (2018); Doyle (2018); Lamba and Singh (2018); Merendino et al. (2018); Thirathon et al. (2018); Victor and Rao (2018);
	Practical model to use and integrate big data/analytics	Tools for integrated architecture	Iot Storage systems Machine learning Cognitive computing systems	Horita et al. (2017); Ji et al. (2017); Storey et al. (2017); Saggi and Jain (2018); Brous et al. (2019)

Source: author's elaboration

5. Discussion

The systematic literature review highlights the existence of different strategic approaches to the integration of Big Data into business decision-making that identify diverse levers to foster effective decision-making, from managerial commitment and support to the creation of a data-driven environment. Then, at a process level, these strategies should be turned into active resources and skills to be integrated in order to extract relevant information from big data and to obtain new knowledge and potential insights to address problems or adopt a proactive mind-set to challenge complexity (Polese et al., 2016). Finally, organizations can benefit from a data-oriented mind-set to generate value throughout the entire supply chain, from service/product quality to the relationships with customers.

For this reason, the most relevant implication of the analysis is that the strategic inclusion of big data into organizational structure (strategy) should be translated into related integrated process (operations) based on an integrated technological architecture.

As figure 4 shows, the findings obtained through the exploration of strategic dimension (RQ1) can be associated with the results an operational level (RQ2).

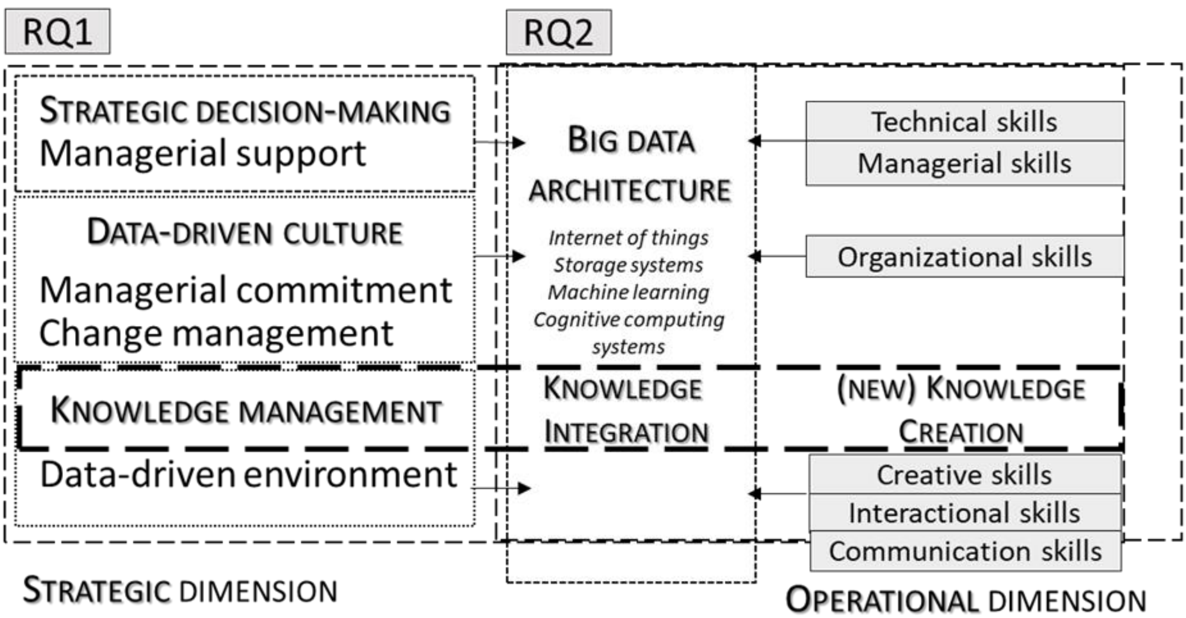
Some relationships between a strategic and operational level can be identified to reveal how the strategic levers can be translated into active knowledge thanks to the application of a varied set of skills (Barile et al., 2015) to business process that can foster, at the end, the production of (new) knowledge to improve decision-making constantly.

This integrated process can start from the adoption of a data-oriented mind-set (*strategy*) that, thanks to management's attitude and the adoption of a data-culture and the creation of a proper data-driven environment, can lead to the implementation of an integrated architecture based on a combined set of analytics (*technological architecture*). The "activation" of the strategic lever, thus the implementation of management practices and of data-driven environment can be turned into the application of specialized competencies (*management, technical and organizational skills*) in order to generate information flows (*communication and interaction skills*) from which relevant knowledge can be extracted (*creative skills*).

If strategic decision-making seems to be related to the activation of managerial skills and leadership attitude, data-driven culture seems to require a broader organizational change that redefines the entire business orientation to include big data. Thus, the main principles of knowledge management can be associated mostly to the activation of soft skills that allow managers at going beyond the use of analytical thinking to develop creativity.

The common thread of the entire process is knowledge (in the middle of the figure) that acts as a strategic driver, as enabler of collaborative synergies (Elbashir et al., 2013) between the different departments and as output of a successful data extraction, for the improvement of decision-making and the potential emergence of innovative solutions. Knowledge integration through technological instruments cannot produce relevant or new knowledge without the intervention of hard and soft skills that facilitate information sharing, simplify information flows and create a learning orientation targeted at the exploitation of creativity (Polese et al., 2018). Therefore, decision-making effectiveness stems from the proactive identification of unexpected solutions.

Figure 4. Synthesis of results: big data for decision-making at a strategic and operational level



Source: author's elaboration

6. Concluding remarks

The work detects the main strategic approaches to big data analysis proposed in literature to reframe decision-making and proposes a categorization of the key strategic and operational levers for an effective application of big data analysis and analytics to improve business processes.

The findings show that the implementation of a big data architecture can benefit from the adoption of a data-oriented mind-set that should be translated into the activation of hard and soft skills that cam extract relevant knowledge to generate multiple advantages throughout the entire supply chain, from service and product improvement to the enhancement of internal and external relationships. Thanks to an integrated architecture and to the application of analytical, critical and creative skills, firms can exploit the advantages offered from big data analytics to increase competitiveness, simplify knowledge exchange and communication flows, engage users and develop innovative solutions.

From a theoretical viewpoint, the work provides an original perspective to understand the conceptual evolution of the issue of decision-making after the introduction of big data. Moreover, the study allows gaining a wider awareness about the features that should be taken into account to manage the large amount of organizational data properly. The article highlights how the use of analytics according to a data-driven mind-set can help overcoming the limitations of big data, such as heterogeneity or untruthfulness (Gupta and George, 2016). Moreover, the study can represent a first theoretical step for the conceptualization of the main drivers for big data implementation, of the right skills to manage big data and on BDA tools.

The study proposes some relevant insights for managers, by highlighting the potential of digital revolution to change deeply management and decision-making practices according to a new data-driven culture (Chen et al., 2012). The work suggests that, through a strategic approach to big data and through the application of hard and soft skills to the use of analytics, it is possible to gain a better and immediate comprehension of business opportunities, on costumers' behaviour, on service/ product effectiveness (Lager, 2010) thanks to the continuous generation, analysis and interpretation of data that can be turned into information and relevant knowledge. Thus, the classification of the strategic levers and of the right skills to benefit from big data application to decision-making can help managers identifying the main enabling elements to be strengthened to improve effectiveness of decisions, to increase users' engagement and to enhance organizational knowledge.

However, the work is conceptual and cannot allow at drawing any generalization of results. For this reason, it can be intended as a first exploratory step for the subsequent proposition of empirical research that can start from the investigation and redefinition of the key drivers identified. The main strategic drivers and the classification of data analysis skills can be assessed in specific organizational context through case study (maybe by using the drivers as leading themes in an interview sheet) or through quantitative techniques (by proposing the measurement and the relationships between constructs such as management skills, big data use and decisions effectiveness or potential innovation).

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Appendix A - Analysis sheet for content analysis

MACRO- STRATEGIC LEVEL (RQ1)
Topic 1: *Observation of a strategic orientation*
❑ strategic inclusion of big data into business strategies (present/missing);
❑ strategic inclusion of big data into decision-making (present/missing);
❑ proposition of a specific viewpoint on big data;
❑ introduction of a conceptual framework- business cycle.

Topic 2: Key strategic lever for big data orientation to decision-making
❑ identification of strategic objectives-phases of big data inclusion into decision-making;
❑ introduction of specific classification of big data strategies.

MICRO-OPERATIONAL LEVEL (RQ2)
Topic 3: Operational drivers for the implementation of big data analysis and analytics
❑ classification of the main drivers for big data implementation;
❑ identification of resources and skills to use big data;
❑ categorization of the technological tools and analytics for big data architecture;
❑ identification of big data implications on business process and/or operation;
❑ proposition of models with the identification of the main resources-tools for big data application.

Appendix B – Variables, keywords and main categories identified in content analysis

	Keywords	**Final categories identified**
RQ1		
Strategic approach	Strategy Culture Beliefs Changes Leadership Decision-making Strategic management Mind-set	Strategic decision-making Human Proactiveness Teamwork Data-driven culture Knowledge Knowledge management Innovation-oriented attitude
Strategic levers	Resources Capabilities	Top management support Commitment

	Management attitude	Change management Data-driven environment
RQ2		
Operational drivers	Technologies Analytics Big data Big data analytics Information and communication technologies Platforms Social networks Platforms/Tools Data Mining	Management skills Technical skills Data analysis skills Integrated architecture Iot Cognitive computing Databases Machine learning Cloud computing systems Decision support systems