

# Discovering the Relationship Between Big Data, Big Data Analytics, and Decision Making: A Structured Literature Review

Daniela Di Berardino, Associate Professor in Business Administration Simone Vona, PhD in Accounting, Management and Business Economics University of Chieti-Pescara, Italy

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## **Abstract**

This paper focuses on providing a structured literature review on the role of Big Data (BD) and Big Data Analytics (BDA) in supporting decision making. The study aims to systematize the knowledge, the primary results, and research gaps related to BD and BDA in strategic management and in decision making by providing a future research agenda. Adopting the methodology of Massaro et al. (2015), the structured literature review investigates this phenomenon analyzing a sample of 97 articles published in high-level scientific journals ranked in ABS list in the Marketing, Strategic Management, Ethics, Gender, and Social Responsibility area. Bibliometric analysis, content analysis, and the PRISMA protocol have been used for the review. The study unveils the subject of decisions, factors influencing good decisions, and the main effects of using BD and BDA in decision making. New organizational factors, data chain dynamics, and inhibitors should be explored to remove the obstacles in decision making. The relationship between BD/BDA and decision making remains underexplored in public organizations, non-profit organizations, and small and medium-sized firms.

**Keywords:** Big Data Analytics, Big Data, strategic management, decision making, structured literature review, bibliometric analysis

## Introduction

Big data (BD) research has grown over the last few years intensively. However, the ambiguity about their complete taxonomy and their real effectiveness stimulates an intense scientific debate (Hartmann et al., 2014; George et al., 2016). There is a widespread belief that the implementation of BD generates, above all, many organizational benefits, such as operational efficiency and innovation (McAfee et al., 2012; Gobble, 2013), as well as competitive advantage (Sivarajah et al., 2017). However, how BD could improve strategic decisions require further validation and exploration (Abbasi et al., 2016; Erevelles et al., 2016). This makes it possible to empirically verify the potential of these resources by analysing the factors influencing their efficient use in decision making.

Literature shows multiple definitions of BD, high incidence of interdisciplinary studies, and the absence of a common theoretical framework in management and accounting studies (Elia et al., 2020). Many studies define BD as a massive and complex amount of data sets (volume), which is acquired and delivered in real time (velocity) through different sources, structured and unstructured (variety), such as social media, web pages, commercial transactions, image and video downloads, clinical trials, geotagging, output from sensors, and other smart technologies (Laney, 2001; Johnson, 2012; McAfee et al., 2012; Fredriksson, 2015; Gandomi & Haider, 2015; Fosso Wamba et al., 2015). Some scholars define BD as a cultural, technological, and academic phenomenon based on the interaction of technology and analysis (Boyd & Crawford, 2012). This definition refers to the tools and processes that can transform such data into strategic resources with high potential. Furthermore, it refers to the mythological belief, partially validated in literature, which states that «large data sets offer a superior form of intelligence and knowledge capable of generating previously impossible insights, with the aura of truth, objectivity, and accuracy» (Boyd & Crawford, 2012).

Considering the managerial implications of BD paradigm, a second set of properties emerges in literature, namely: veracity and value (White, 2012; Gandomi & Haider, 2015). Veracity refers to the integrity and accuracy of data that can be uncertain or problematic (Alles & Gray, 2016), especially when it is not monitored by proper analytic tools. Value in big data studies refers to the potential in supporting decision making (Goes, 2014) and the business model design (Fosso Wamba et al., 2015), which enhances improvement in performance (McAfee et al., 2012) and product innovation (Mayer-Schönberger & Cukier, 2013).

However, many firms have not yet successfully leveraged Big Data (BD) to transform their business functions (Chen et al., 2015; Sanders, 2016). Other BD's ontological properties have been added during the time (Kitchin

& McArdle, 2016), including the technological aspects. Considering the organizational context, many factors and processes, which may affect the BD and the BDA implementation in the firm, request more analyses. BD offer a wide range of social and economic knowledge, which emphasizes the value of perceptive and predictive models to support business decisions (Dubey et al., 2019).

Strategic decision making is a process of making choices under different levels of uncertainty (Milliken, 1987; Petrakis et al., 2016) and the lack of information enhances this uncertainty (Merendino et al., 2018). BD can reduce this lack by providing a large set of information. This in turn will reduce cognitive bias and improve decision making. However, directors need to develop new capabilities to perceive, analyse, and use this data in strategic decisions. The real value of BD is extracted through the Big Data Analytics (BDA), a branch of Business Intelligence that is structured in technologies, analysis processes, and architectures, which is designed to implement BD. Subsequently, this allows companies to develop innovative managerial approaches and decision making that improve the organizational performance (Davenport, 2006; Chen et al., 2012). BD and BDA are independent but interrelated concepts (Alles & Gray, 2016).

Literature shows that BD increases the automation of operations and strategic decision making (Markus, 2015). However, these processes require human judgment and are influenced by managers' behaviour (Newell & Marabelli, 2015). Some authors unveil the risk of confirmation bias, which occurs when managers use only data to confirm their hypotheses and mainly to justify their decisions (Namvar & Cybulski, 2015; Bholat, 2015). Research efforts have mainly focused on technological issues and, recently, on the value creation processes which represent the real benefit of BD and BDA (Günther et al., 2017; Mazzei & Noble, 2017; Elia et al., 2020). The fragmented nature and the high interdisciplinarity of these subjects call for a systematization of the research carried out along time on BD, BDA, and strategic management, especially the implementation of these technologies in supporting strategic decision making.

Therefore, this study aims to provide a structured literature review (SLR) to unveil the scientific knowledge on this topic, the research gaps, and to provide future research. This study further aims to contribute to the literature by analysing the evolution of strategic management studies published in relevant scientific journals in management area. The inductive analysis and discussion are based on a grounded theory approach (Wolfswinkel et al., 2011), where discussion has been coded using open coding and selective coding protocol. The research findings inform practitioners and academics about the main application and factors influencing the BD implementation for strategic decisions, which provides some insights

about future research needs. The remaining part of the paper is structured as follows: Section 2 shows the methodology, Section 3 presents the results in terms of descriptive statistics and bibliometric analysis, Section 4 details critical discussions about the main research themes, gaps, implications, and future research. Finally, conclusions were drawn.

## Methods

To systematize the scientific knowledge, content analysis and structured literature reviews are functional tools to investigate BD phenomenon, considering the high level of interdisciplinarity of this subject and the information asymmetry generated between different conceptual frameworks (Tranfield et al., 2003). The methodology codified by Massaro et al. (2015) was adopted to perform a replicable study. This methodology is articulated in the following phases:

- 1) Definition of the research questions.
- 2) Development of research protocol to conduct the review.
- 3) Development of the coding framework.
- 4) Selection of articles to be included in the revision.
- 5) Codification of the articles.
- 6) Analysis and critical discussion of the results.

The first research question aims to reconstruct the current knowledge, while the second question outlines the theoretical approaches adopted over time and the emerging gaps. Finally, the third question addresses the possible directions of future research (Massaro et al., 2015). Adopting this approach, the following research questions were identified:

RQ1: How is BD/BDA literature developing according to the role of these technologies in orienting the business strategies and decision making?

RQ2: What are the scientific implications and emerging gaps in Strategic Management studies?

RQ3: What are the possible future directions for research?

In the second step, a research protocol was defined and sources, tools, and methods of extraction of the articles to be included in the study were identified (Massaro et al., 2015). Furthermore, the principles of the PRISMA protocol was applied (Page et al., 2021). A coding framework was defined to analyse the articles, following these categories: a) timing of publication; b) journals; c) relevance of paper through citation analysis; d) geographic distribution of research; e) academic and professional papers; f) relevant keywords and themes.

A bibliometric analysis has been performed to verify the co-occurrence between relevant keywords by identifying the main links between concepts and the relevant thematic clusters in BD and BDA research. This analysis has

been processed using VOSViewer software to reduce errors at methodological level (Van Eck & Waltman, 2014).

The keywords identified for the first extraction include the following: "big data" OR "business analy\*" OR "big data analy\*", which leads back to "business analytics", "business analysis", and "big data analysis" or "big data analytics". The research was conducted using the keywords entered in "anywhere", "title", "abstract", and "keywords" to allow the reviewers to have a first perception of the relevance of the articles. Although the extraction of the sample to the international journals, ranked at 3 and 4 stars, was limited in the Academy Journal Guide, it was provided by the Charted Association of Business Schools (ABS) and included only high-level scientific contributions. This classification is in accordance to the well-known ranking from one to four stars. In addition, only the academic journals in the areas of Marketing (MKT), Strategies (STRAT), General Management, Ethics, Gender, and Social Responsibility (ETHICS-CSR-MAN) were considered as summarized in Table 1.

## Table 1. Journal sample

## Strategy (STRAT)

- Ranking 4\*: Strategic Management Journal.
- Ranking 3: Global Strategy Journal; Long Range Planning; Strategic Organization. Marketing (MKT)
- Ranking 4\*: Journal of Consumer Psychology; Journal of Consumer Research; Journal of Marketing; Journal of Marketing Research; Journal of the Academy of Marketing Science; Marketing Science.
- Ranking 4: International Journal of Research in Marketing; Journal of Retailing.
- Ranking 3: European Journal of Marketing; Industrial Marketing Management; International Marketing Review; Journal of Advertising; Journal of Advertising Research; Journal of Interactive Marketing (formerly JDM); Journal of International Marketing; Journal of Public Policy and Marketing; Marketing Letters; Marketing Theory; Psychology and Marketing; Quantitative Marketing and Economics.

General Management, Ethics, Gender, and Social Responsibility (ETHICS-CSR-MAN)

- Ranking 4\*: Academy of Management Journal; Academy of Management Review; Administrative Science Quarterly; Journal of Management.
- Ranking 4: Academy of Management Annals; British Journal of Management; Business Ethics Quarterly; Journal of Management Studies.
- Ranking 3: Academy of Management Perspectives; Business and Society; California Management Review; European Management Review; Gender and Society; Gender, Work and Organization; Harvard Business Review; International Journal of Management Reviews; Journal of Business Ethics; Journal of Business Research; Journal of Management Inquiry; MIT Sloan Management Review.

Articles have been extracted through EBSCO, Scopus, and Web of Sciences platforms to include all items of selection. In the query, the focus is to explore, in the first step, all papers related to BD and BDA in these research areas. As a result, the research is not limited to a defined period in order to have a longitudinal vision of the phenomenon. The extraction has been conducted using papers published up to January 2021 and 2,310 articles were collected. The following have been excluded: editorials, comments, abstract collections, interviews, book reviews, and documents containing only information relating to the authors. In addition, editorial editors present in the sample extracted reduced to 1,543 contributions.

The keyword for the second extraction was "decision making" OR "strategic decision\*", which reduced the sample to 203 articles. Subsequently, the abstracts were read and those articles not related to strategic management and decision making were eliminated. Accordingly, a final sample of 97 articles was generated.

Furthermore, descriptive analysis is provided, alongside the coding protocol, to identify the evolution of scientific contributions over time, the distribution between countries, the analysis of the impact of the citation index (CI), the citations per year (CPY), and the relevant authors. Through the bibliometric analysis, the co-occurrences between keywords have been explored by identifying the main thematic clusters and the relevant conceptual networks (Massaro et al., 2015). Using the authors' keywords, the network analysis of co-occurrence (van Eck & Waltman, 2009) have been performed through visualising articles where these keyworks occur together at least 3 times. Furthermore, this technique has been combined with the cluster analysis (Kessler, 1963) by visualising those articles with high number of similar references and similar subject. The thematic networks has been identified (Newman, 2004) through unveiling the distances between nodes (themes) and visualising those thematic clusters that reduce this distance. Also, content analysis has been performed for the final sample, (Broadbent & Guthrie, 2008; Massaro et al., 2015) alongside the following definitions: the content of the study, the theories applied, the methodology adopted, the research findings, and limitations. Both authors have analysed the sample separately to validate their findings and the identification of relevant research theme through the PRISMA protocol.

# **Results: Literature Development**

The scientific production on BD and BDA, in the sample, presents a fluctuant distribution of publications from 2012 to 2021 (Figure 1), with relevant growth in 2016 and 2019. This discontinuity reflects the contextual weak implementation of BD and BDA in the firm (Ardito et al., 2019).

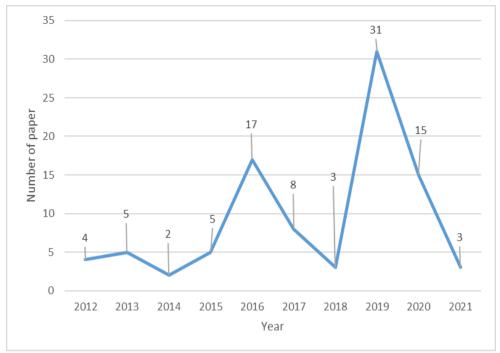


Figure 1. Timing of publication

The main part of the articles (Table 2) of the sample (57%) has been published in General Management, Ethics, Gender, and Social Responsibility area (ETHICS-CSR-MAN). This is followed by Marketing (MKT) and Strategic Management area (STRAT). The most prolific journals (Table 3) include the Journal of Business Research, with 22 scientific papers, Industrial Marketing Management (21 articles), and the professional journals Harvard Business Review and MIT Sloan Management Review, with 14 and 9 contributions, respectively. Journals belonging to the STRAT area, in ten years, show only 2 contributions, published in the Journal of Strategic Organization and 1 article in Long Range Planning. This distribution is attributed to the interdisciplinarity of the subject and its practical implications, which results in its treatment being linked to the transversal General Management, Ethics, Gender, Social Responsibility area, and Marketing.

The citations analysis provides more understanding on the impact of scientific production on BD and BDA in management literature, which unveils the quality of research (Crossan & Apaydin, 2010).

Table 2. Research fields

Tuble 2. Research fields					
Journal ranking					
No.papers	4*	4	3	%	No.citations
3	0		3	3%	2253
37	6	5	26	40%	1460
53	0	6	47	57%	16909
93	6	11	76	100%	20622
	No.papers 3 37 53	No.papers 4* 3 0 37 6 53 0	No.papers 4* 4 3 0 37 6 5 53 0 6	No.papers 4* 4 3 3 0 3 37 6 5 26 53 0 6 47	Journal ranking           No.papers         4*         4         3         %           3         0          3         3%           37         6         5         26         40%           53         0         6         47         57%

**Table 3.** Distribution of papers across the Journals in management area

Table 3. Distribution of pape		ABS	No. of
Journals	Research Field	Ranking	articles
Journal of Consumer Research	MKT	4 *	1
Journal of Marketing	MKT	4 *	3
Journal of the Academy of Marketing Science	MKT	4 *	1
Marketing Science	MKT	4 *	1
International Journal of Research in Marketing	MKT	4	2
Journal of Retailing	MKT	4	3
British Journal of Management	ETHICS-CSR-MAN	4	5
Business Ethics Quarterly	ETHICS-CSR-MAN	4	1
Long Range Planning	STRAT	3	1
Strategic Organization	STRAT	3	2
European Journal of Marketing	MKT	3	2
Industrial Marketing Management	MKT	3	21
International Marketing Review	MKT	3	1
Journal of Advertising	MKT	3	1
Marketing Letters	MKT	3	1
California Management Review	ETHICS-CSR-MAN	3	2
Harvard Business Review	ETHICS-CSR-MAN	3	14
Journal of Business Research	ETHICS-CSR-MAN	3	22
MIT Sloan Management Review	ETHICS-CSR-MAN	3	9

Untill 2021, the distribution of citations (Figure 2) unveils a decreasing trend of three peaks in 2012, 2016, and 2019. Although it was updated on April 9, 2022, the most cited studies are linked to General Management, Ethics, Gender, and Social Responsibility area. The strategic area shows studies with a greater influence, with 2253 total citations. This is in contrast to the most prolific marketing area that receives 1460 citations. Using CI index (Table IV), the most influential paper is McAfee et al. (2012). This is followed by Sivarajah et al. (2017), Fosso Wamba et al. (2016), Erevelles et al. (2016), and Davenport et al. (2012). These studies focus on investigating the challenges that affect organizations in implementing techniques, technologies, and analysis methods in BD through strategic skills extraction in capturing value and opportunities from data. These results are partly confirmed through the

citation parameter per year (CPY). However, the only variation is the ranking for the article of Wedel and Kannan (2016), with a study that focuses on examining the analytics available in organizations to support marketing decision making.

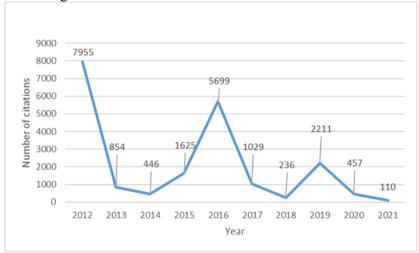


Figure 2. No. of Citations

Table 4. Most cited papers

Author (-s)	Title	CI	CYP	Journal
	Big data: The management			Harvard
McAfee et al. (2012)	revolution	6793	672,67	business review
	Critical analysis of Big Data			Journal of
	challenges and analytical			Business
Sivarajah <i>et al.</i> (2017)	methods	1919	314,80	Research
	Big data analytics and firm			Journal of
	performance: Effects of			Business
Fosso Wamba et al. (2016)	dynamic capabilities	1517	225	Research
	Big Data consumer analytics			Journal of
	and the transformation of			Business
Erevelles et al. (2016)	marketing	1388	184,50	Research
Davenport et al. (2012)	How big data is different	1195	102	MIT Sloan MR
r	Marketing analytics for data-			Journal of
Wedel and Kannan (2016)	rich environments	861	138	Marketing

While observing the authors' affiliation, the geographical distribution of the countries have been analysed based on the collaborations between the authors (Figure 3). The count was made by considering the presence of a country in the authorship. Therefore, each country involved in the article received one point. The most productive country is the USA with 50 articles. This is followed by UK and France, with 28 and 10 references, respectively. This data unveils the intense interest of Anglo-Saxon' scientific community in

this research field. However, considering the size of geographical macroregions, Europe, with 66 articles, is a relevant scientific community on this theme, alongside North America (56 articles) and Asia (16 articles).

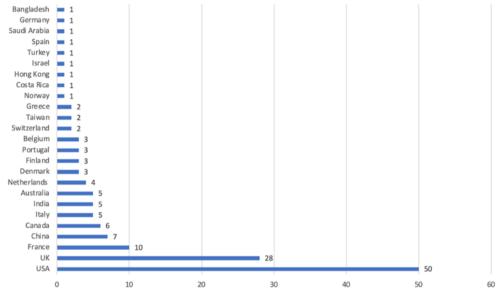


Figure 3. Geographic distribution of research

This observation has been integrated in order to distinguish between academics and professionals. In the sample, 22% of the studies involves authors from the non-academic world. Specifically, 9.7% of the sample presents one professional author, while 4.2% is composed of two and more non-academic authors. However, a large part of literature is derived from academics, which shows a strong scientific footprint in the knowledge development in this subject.

## **Discussion: The Main Research Themes**

A bibliometric analysis combined with a cluster analysis has been conducted through a study of the co-occurrences of the keywords belonging to the contributions of the sample. The analysis of the occurrence of keywords can be used to create co-words maps (Figure 4) that show the correlations between the main themes investigated in this research domain, thus adopting a grounded theory approach for the inductive analysis. The cluster technique was performed (Van Eck & Waltman, 2009, 2014) using the VOSviewer software. This sets the counting method as "full counting" since the documents in the keywords occurred at least twice (threshold). Table 5 shows the 25 keywords merged according to the recurrence in the sample and 4 different clusters. The most used keywords are Big Data (30), Big Data Analytics (15), Firm performance (6), and Decision Making (4). Figure 5 shows the ties

between the research themes and the distance between them. Also, an association exists between the themes "decision making", "value creation", "capabilities", and the "knowledge-based view". The blue cluster connects with the red and yellow clusters with the term "Big Data" (red cluster), which is the central element of this survey. The red cluster includes the words "Analytics", "Artificial intelligence", and "Machine Learning" and it focuses on technological factors of this subject. The yellow cluster connects "Firm performance", analytics", "Marketing and "Customer relationship management", while the "Dynamic capabilities" (purple cluster) turns out to be a concept related to the studies concerning "Firm performance", "Data analytics" (purple cluster), and the "Big data Analytic" (green cluster). The enabling organizational factors of "Capabilities", "Decision making" and "Value creation" are investigated seperately from technological factors such as "Artificial intelligence" and "Machine learning", including factors related to "Business Performance" and "Marketing Analysis". This analysis unveils that the main theoretical issues that have been highlighted by authors' keywords are the knowledge-based view, the dynamic capabilities, and the complexity theory.

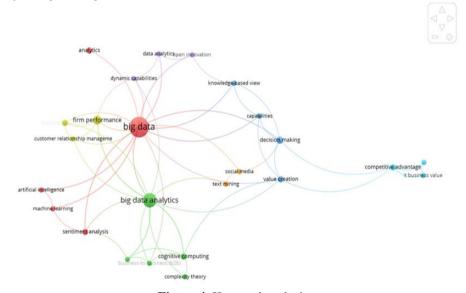


Figure 4. Keyword analysis

The content analysis, performed through Nvivo Software and reading the papers, shows two main isolated research themes using the matrix with cowords occurrencies and the weighted percentage of references' coverage. The first theme identifies the organizational benefits generated through the BD/BDA applications, while the second theme focuses on the relationship between the BD/BDA and the decision-making process (Table 5).

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**Table 5.** Main themes in management studies

	Themes	Table 5. Main themes in managen  Key features	Main papers
BD/BDA organiza		Market responsiveness Competitive advantage Cost saving Customer relationship Management Customer experience Revenue growth Supply chain management and retailing Knowledge management Open innovation Pricing Decision making Human resource management Detecting crisis	Woerner and Wixom, 2015; Erevelles et al. 2016; Bradlow et al. 2017; Côrte-Real et al. 2017, 2019; Ren et al. 2017; Sumbal et al. 2017; Toubia and Netzer, 2017; Wamba et al. 2016; Chen et al. 2019; MIkalef et al. 2019a; 2020; Ghasemaghaei and Calic (2019); Elia et al. 2020; Holmlund et al. 2020; Yasmin et al. 2020; Zhang H. and Xiao, 2020; Zheng et al. 2020; Zhang C. et al. 2020; Stourm et al. 2020; Hajili et al. 2020; Holland et al. 2020; Hung et al. 2020; Steinberg et al. 2020; Farrokhi et al. 2020; Steinberg et al. 2020; Brinch et al. 2021; Du et al. 2021; Zhang Y et al. 2021
	A and decision- process:		
a)	Effects	Cognitive overload and cognitive bias Greater individual skills Internal tension managing excess of data Greater responsibilities in the board Predictive decisions Corporate governance dynamics	Merendino et al. 2018; Janssen et al. 2017; DalleMule and Davenport, 2017; Troisi et al. 2020; Van Rijmenam (2019); Kauffman et al. 2020; Liu et al. (2017; 2020); Jabbar et al. (2020)
<i>b)</i>	Factors influencing good decisions	Internal co-ordination between decisors Strong collaborations with external experts and BD providers High individual BD capabilities Knowledge transfer on BD and BDA Clear contracts and procedures in BD sourcing Integration and standardization in BD chain Accurate data Structural factors (infrastructures, organizational culture)	Tobaccowale and Gupta (2016); Janssen et al. (2017); Davenport and Bean (2018); Merendino et al. (2018); Lin and Kunnathur, 2019; Mikalef et al. (2019b); Parra-Moyano (2020); Yasmin et al. (2020)
c)	Subject of decisions	Marketing strategies Organizational strategies Sustainable policies	Chen et al. (2019); Hajili et al. (2020); Jabbar et al. (2020); Gnizi (2019);

Human Resource Management Innovation policies

Kauffman et al. (2020); Toubia and Netzer (2017).

Although managerial literature considers interrelated concepts of BD and BDA, the technological differences related to the resources (BD) and the processes (BDA) are neglected. A large set of articles explore the contribution of BD and BDA in marketing decisions and marketing activities. Furthermore, theoretical and empirical papers unveil many uses of these technologies and the related dynamic capabilities in improving customer experience (Holmlund et al., 2020), market analysis, market sensitiveness, and customer loyalty programs (Erevelles et al., 2016; Liu et al., 2017, 2020; Holland et al., 2020; Kauffman et al., 2020; Stourm et al., 2020; Zhang et al., 2020; Du et al., 2021). Other studies exploit the contribution of BD and cognitive computing in managing supply chain relationships and retailing (Sanders, 2016; Bradlow et al., 2017; Dekimpe, 2020; Hung et al., 2020; Martin et al., 2020; Zheng et al., 2020), promoting open innovation, orienting pricing policy and product development (Toubia & Netzer, 2017; Chen et al., 2019; Mikalef et al., 2019b, Steinberg, 2020; Zhang & Xiao, 2020), and detecting crisis (Farrokhi et al., 2020). The rationale of these studies is to explore the usefulness of BD and BDA in contributing to business performance by verifying the mediating role of dynamic capabilities. Few papers empirically verify this relationship through survey or multiple case study methods.

Even if these researches show that BD amplify the dynamic capabilities that are useful to improve financial performance, there are ambiguous findings around the nature of these capabilities. While some papers unveil the greater role of infrastructures and human resources skills (Fosso Wamba et al., 2016; Hajli et al., 2020; Salvi et al., 2021), other papers consider only managerial skills and organizational factors as relevant (Mikalef et al., 2019b; Parra-Moiano et al., 2020; Yasmin et al., 2020; Brinch et al., 2021). Recent literature reviews (Günther et al., 2017; Batistič & van der Laken, 2019; Elia et al., 2020) systematize the literature on BD and performance to reveal other organizational benefits such as cost saving and productivity (Ren et al., 2017) profitability, cost leadership and revenue growth (Woerner & Wixom, 2015; Côrte-Real et al., 2017, 2019; Mikalef et al., 2019a, 2020), which improve knowledge management activities (Sumbal et al., 2017) and innovation capabilities (Ghasemaghaei & Calic, 2019).

Other conceptual papers explore new research agenda in managerial sciences on the role of BD in innovation strategies (Sheng et al., 2017, 2020). These studies suggest exploring new trends in human resource work conditions, customer behaviours, and web marketing experiences so as to observe how BD could enhance sustainability in supply chain management and product development. Only a paper in the sample studies the public sectors to explore the ability of BD in improving the quality of care in health

organizations (Wang et al., 2019). Private company remains the main organizational setting explored.

Based on the role of BD and BDA in supporting strategic decisions, this research confirms a large set of conceptual papers that exploit the potential of BD in improving decision making. Many papers refer to the relationship between these technologies and decision making in uncertain contexts (Van Rijmenan et al., 2019; Gnizy, 2019) by exploring factors fostering good decisions (Shah et al., 2012; Schrage, 2016; DalleMule & Davenport, 2017; Janssen et al., 2017; Davenport & Bean, 2018; Zeng & Glaister, 2018; Merendino et al., 2018) or suggesting new theoretical perspective anchored to BD capabilities (Lin & Kunnathur, 2019).

Oldest papers provide theoretical contribution about the cause-effect relationship between BD, BDA, and good decisions. On the other hand, recent studies empirically explore this relationship through qualitative research methods that involves CEO or IT managers. The main findings show the presence of inertia and a cognitive overload on individual directors generated by excess data. To solve this situation, a common BD culture among decision-makers and strong internal co-ordination and BDA capabilities are essentials. Scepticism on data, team compositions, and historical knowledge (Schrage, 2016) influence managers in decision making. Sometimes, organisations respond proactively by developing internal BD capabilities or collaborating with external experts and providers of data (Merendino et al., 2018; Lin & Kunnathur, 2019).

Janssen et al. (2017) highlight many factors that could influence the decision-making process based on BD and BDA. These factors include the following: BDA capabilities and knowledge transfer about data; collaboration between BD providers, decision-makers, and BD analysts; clear contracts, transparent procedures, and responsibilities between the firm and the BD providers; integration and standardization of BD chain; and accurate data and skilled decision makers. Other qualitative papers on data strategy provide theoretical framework (DalleMule & Davenport, 2017) or case study (Troisi et al., 2020). The professional paper of DalleMule and Davenport (2017), published on Harvard Business Review, show a theoretical framework that aims to address companies in strategic data management due to the trade-off between the defensive and the offensive approach. The authors define the offensive strategies more flexible and focused in supporting the organizational performance, through activities such as data analysis and data modelling, with the aim to improve the customer insights and support decision making. Conversely, defensive strategies are standardized and aimed to ensure data security and quality and reduce data risks through activities such as data privacy, the use of analytics to detect the data fraud, and the control of data

structure. However, this contingent approach, developed on a single case study, is not verified in literature.

Using the action research methodology, Troisi et al. (2020) confirm the usefulness of BD in accelerating innovations, strategic decisions, and improving managerial capabilities. However, the large amount of data is difficult to be managed and understood and decision makers may loss relevant knowledge when it is not clear how BDA generates certain results (Günther et al., 2017). Other papers explore the role of BD and BDA in addressing organizational strategies (Nunan & Di Domenico, 2017), specific marketing strategies (Jabbar et al., 2020; Kauffman et al, 2020; Hallikainen et al., 2020), human resource management policies (Zhang et al., 2021; Gupta et al., 2020), and sustainable policies (Sivarajan et al., 2020). The main theories applied in interpreting this phenomenon include the knowledge-based view of the firm, the dynamic capabilities theory, and the resource-based view. These theories focus the analysis on the internal factors that can sustain the firm's competitive advantage, thus confirming the theoretical premises. Other managerial theories include affordance theory of Gibson (1979), the actor network theory, the complexity theory, and the organizational learning theory.

# **Research Gaps and Future Directions**

Literature in the main scientific journals in management studies unveils few longitudinal research and quantitative studies to generalize the findings. Several studies explore single or multiple case studies by providing contingent research findings. A recent paper, not included in the sample, shows the positive relationship between dynamic capabilities and decision making quality in a sample of 240 agricultural firms (Li et al., 2021). However, this quality has been measured using a static model and categorical variables with a mean value close to neutral value of 3 and a Likert scale ranging from 1 to 5. The main perspective is the application of BD/BDA to observe the internal processes. However, it neglects the supply chain of data, as well as the external dynamics between managers and data suppliers. Many papers explore the customer engagement in BDA to gain usefulness in decision making, while the role of providers remain underexplored.

Other limitations identify the overlap between similar themes, such as machine learning and artificial intelligence, cognitive computing, analytics and BD, which requests an integrate perspective of the phenomenon through a clear taxonomy of these technologies. Few studies observe this subject in developing countries or explore the relationship between BD/BDA and the social and environmental issues. Private company remains the main organizational setting explored, while the support and the dynamics of BD/BDA in decision making in public administration or non-profit

organizations are unclear. Similarly, the SMEs or the family firms are underexplored.

The mediating effect of some organizational factors, such as the corporate governance features, the organizational culture or the leadership style might be explored to verify how they contribute to leveraging BD and BDA to improve decision making. Organizational theories might constitute a fertile area to explore the cultural drivers or barriers in the BD/BDA application for decision making. Similarly, Intellectual Capital perspective might provide a strategic and systemic point of view of this phenomenon (Secundo et al., 2017). BD and BDA are relevant intellectual assets that might generate profitability and the Intellectual Capital perspective considers both the internal capabilities and the external relationships between the firm and the strategic stakeholders. Inhibitors factors deserve attention to remove the obstacles in decision making, especially those factors related to the difficulty in managing the overload of data and the integration between the providers and the firm's infrastructures in the BD chain. Opportunistic behaviours and resource-dependency dynamics in BD supply chain might be explored in future studies.

## **Conclusion**

Nowadays, big data cover a growing interest in the research agenda of academics and practitioners. How BD and BDA improve the decision-making process and the competitive advantage of the firm deserves in-depth exploration. Behind the high potential theoretically stated, the knowledge regarding how these technologies and resources are implemented is linked to few case studies related to big companies. On the other hand, there is a small percentage of success in SMEs,. Therefore, the main inhibitory factors which managerial and organizational approaches could make efficient, such as the decisional processes, deserve more investigations.

Nonetheless, this SLR's contribution is twofold: a) to systematize the relevant literature and research findings for academic, inspiring future research issues on this subject; b) to identify useful operational implications to managers engaged in implementing and exploiting BDs, which will highlight the main results and inspire new behaviours regarding their use. This SLR shows that the literature on BD and strategic decisions is still in a stage of understanding the phenomenon and capturing the impact of the characteristics, factors, applications, and dynamics related to their use in strategic decision making. Some conceptual papers have been validated through empirical surveys by suggesting a new research stage in BD literature. Future studies need to maintain the interdisciplinarity perspective due to technical factors, alongside organizational and managerial factors that influence the effective implementation of BD and BDA in decision making.

However, this subject suffers a research trap as many papers try to introduce new theoretical lens and managerial approaches. This has led to an overload of theory without strong validations and practical usefulness of these models. Practical implications of this study refer to those factors that have to be managed to make the firms more agile in implementation of BD. Subsequently, the attention is on BD chain and individual BD capabilities. Internal co-ordination between technical staff and the decision team, more investments in BD education, agile organizational structure, more distance from silos structure, and co-production with providers of data are essential to make the implementation of BD in decision making more effective.

Some limitations of this study can be traced back to the methodological choices made in the literature review, which considered only the top journals in the ABS ranking. Another limitation concerns the exclusion of conference papers and book chapters, where different and interesting research perspectives can be found. Despite using a structured approach for the literature analysis, the inclusion of some articles in the data strategy area in the final sample suffer subjective judgment by operators, which may be due to known decision biases (Fosso Wamba et al., 2015). Therefore, further study is required through a less stringent selection approach, which will create a complete overview of the phenomenon.

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## Appendix A - List of reviewed articles

- Andrew, J. & Baker, M. (2019). The general data protection regulation in the age of surveillance capitalism. Journal of Business Ethics, 1-14.
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