

# The Role of Big Data Analytics in Corporate Decision-making

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**Keywords:** Big Data, Data Analytics, Corporate Decision-making, Systematic Literature Review (SLR).

**Abstract:** Big Data Analytics results can play a major role in corporate decision-making allowing companies to achieve competitive advantage and make improved decisions. This paper describes a systematic literature review (SLR) on the role of the results of Big Data Analytics in corporate decisions. Initially, 1652 papers were identified from various sources. Filtering through the 5-step process, 20 relevant studies were selected for analysis in this SLR. The findings of this study are fourfold in the area of: (a) usage of the results of Big Data Analytics in corporate decision-making; (b) the types of business functions where analytics has been fruitfully utilised; (c) the impact of analytics on decision-making; and (d) the impediments to using Big Data Analytics in corporate decision-making. Also, on the management front, two important issues identified are: (i) aligning data-driven decision-making with business strategy and (ii) collaboration across business functions for effective flow of Big Data and information. On the technical front, big data present some challenges due to the lack of tools to process such properties of Big Data as variety, veracity, volume, and velocity. We observe from this analysis that, thus far, little scientific research has focused on understanding how to address the analytics results in corporate decision-making. This paper ends with some recommendations for further research in this area.

## 1 INTRODUCTION

As stated by Johnson (2012), 15 out of 17 industry sectors in the US have more data stored per company than the US Library Congress, which alone collected 235 terabytes of data in April 2011. Big Data Analytics examines a broad range of sources (Reddi, 2013), such as social media, public web, archives, docs, business apps, and others. These sources of data are used in analytics to address business aims: e.g., cost reduction, improving sales strategy, pricing, development of new products and services, improved risk management, and others.

Example decisions rooted in analytics results are attributed to corporate-driven questions, such as: Is there a need for certain new products and services in specific geographical areas? How should we price our products and services? What alternatives to consider? (Davenport, 2014) How much inventory should be held in the warehouse? What kinds of offers should be given to customers with different profiles? (Davenport, 2013).

Koscielniak and Puto (2015), noted that the use of information for making decisions and the way in which it is organized is becoming important. This

view is also supported by results of a survey conducted by McKinsey in 2011 (McKinsey, 2011) which suggests that the analysis of Big Data is potentially becoming a key basis for competition, productivity and innovation. The use of the results of Big Data Analytics in business enables companies to achieve competitive advantage (Kościelniak and Puto, 2015). However, using traditional data to support decision-making is not new: e.g., determining favourite product features based on user preferences (Ziora, 2015) the data for which are gathered during the product evaluation phase to make decisions concerning the new product (Barbaciuru, 2014).

However, Big Data differs from traditional data, principally in several accepted characteristics: Volume, Velocity, Variety and Veracity (Chen et al, 2014). More recently, Value is also added to these characteristics (Wegener and Sinha, 2013). Thus, new and more in-depth information can potentially be derived from Big Data for use in corporate decision-making (Vahn, 2014). In addition, a survey conducted by Capgemini in 2012 (Capgemini, 2012) shows that the participants who have applied data analytics have seen approx. 26% improvement in business performance and they expect to improve this number

to 41% in the foreseeable future. Furthermore, in a study conducted by CSC in 2014 (Infochimps, 2013) with more than 300 IT employees revealed that approx. 52% of the respondents were involved in a Big Data project, and approximately 59% of them rated Big Data Analytics as top 5 priority items for their company.

Yet, IDG Enterprise study presented by Columbus (2015) reveals that 36% of the participated companies have plans to increase their budgets for data-driven initiatives within the organization. As the top priority, 61% of the respondents stated that the main goal in investing in data-driven initiatives within the organization is to improve the quality of the decision-making as they considered Big Data Analytics as an important tool to accelerate and gain important business insight and value from data.

From aforementioned studies, it is clear that Big Data Analytics and corporate decision-making are fermenting in industry while no “tangible body of knowledge” is readily visible in the scientific literature. This situation motivated us to conduct a systematic literature review (SLR) in order to obtain some insight. We ask four key questions under the general banner of the “role of Big Data Analytics in corporate decision-making”, represented by the following core points:

- RQ1 – use of Analytics results in decision-making;
- RQ2 – the business functions involved;
- RQ3 – impact of Analytics on aspects of decision-making process; and
- RQ4 – impediments to using Analytics in decision-making.

The key findings relate to the following:

- RQ1: Approaches on how to use the results in decision making;
- RQ2: Different business functions where the Big Data Analytics results can be used;
- RQ3: the aspects of decision-making process affected by Big Data Analytics; and
- RQ4: (i) Difficult in aligning data-driven decision-making with business strategy and (ii) collaboration across business functions.

Collectively, these findings add tangibly to the current, meagre knowledge base on the role of Big Data Analytics in corporate decision-making. The paper also discusses the implications of these findings on practice and research. Section 2 discusses research methodology; Section 3 describes the results and discussion; Section 4 describes limitations and threats; and Section 5 concludes the paper.

## 2 METHODOLOGY

This section describes the research methodology used in this study.

### 2.1 Systematic Literature Review

A systematic literature review (SLR) is a way of identifying, evaluating and interpreting research relevant to a particular research question, or topic area, or phenomenon of interest, using a revised research method that is reliable, accurate and facilitates auditing (Kitchenham, 2004; Mafra and Travassos, 2006). There are several reasons for undertaking a SLR, for example (Kitchenham and Charter, 2007):

- To summarise the existing evidence concerning a specific area;
- To identify any gaps in current research in order to suggest areas for further investigation;
- To provide a framework/background in order to appropriately position new research activities;
- To examine the extent to which empirical evidence supports/contradicts theoretical hypotheses, or even to help yield new hypotheses.

In this paper, we followed the guidelines suggested by Kitchenham and Charter (2007).

### 2.2 Research Questions

We ask following research questions. Collectively, they address the role of Big Data Analytics in corporate decision-making:

**[RQ1] How are the results of Big Data Analytics used by management in corporate decision-making?** This question is important for characterizing corporate decision making with respect to Big Data usage.

**[RQ2] In which business functions (e.g., marketing, financial, manufacturing, project management, etc.) are the Big Data Analytics results used?** This question helps in characterising business functions and identifying others which could possibly take advantage of Big Data Analytics.

**[RQ3] Which aspects of the decision-making process can be affected by Big Data Analytics?** Brown-Liburd et al., (2015) mention that the decision-making process is composed of elements such as accountability, outcome evaluation, the number of people involved, and the quality of the analysis. To this, we add some other elements, such as information (e.g., inputs, contextual, constraints, timing, deadline, know-how, etc.) on hand to be able

to make the decision; (ii) authority to make the decision; (iii) consequences and impact of making the decision and executing it; etc. So, which elements of the decision making process are affected by the use of Big Data Analytics.

**[RQ4] What are the impediments to using Big Data Analytics in corporate decision-making?**

Understanding the barriers posed by the use of Big Data Analytics for decision making can help in creating new technologies and work processes.

## 2.3 Search Strategy

This section describes the strategy used to conduct the search for primary studies. We used both automatic (electronic databases) and manual searches (business journals and conferences proceedings).

### 2.3.1 Search Terms

In order to ensure that the literature review adheres to the topic of Big Data Analytics and Decision-Making, we limited our search string to the most relevant terms (e.g., Big Data, Big Data Analytics, Corporate Decision Making, corporate Decision, Decision Making, Decision Making process, Decision-making model, business functions, decision) that we extracted from the defined research questions.

We then performed various tests using the identified terms. Approximately five versions of the search string were generated in order to finalise it. The search strings composed by the following terms: (Corporate Decision-Making, Corporate Decision, Decision, Business Functions) returned less relevant results as these terms are commonly used in the business literature (not related to Big Data Analytics).

In order to restrict our research to the most relevant results, we used the following terms and logical operators: ("**Big Data**" OR "**Big Data Analytics**") AND ("**Decision-making Model**" OR "**Decision-making Process**" OR "**Decision-making**")

Despite having the rationale for using the search string above, the terms in it could have failed to identify certain papers (e.g., "large-scale complex systems") that do not use our search terms. This is thus a threat related to this study (see section 4) the extent of which is not knowable without further investigation.

### 2.3.2 Resources

The used resources are divided into: electronic database, business and management, and software

engineering scientific journals and companies' technical reports, also known as white papers. Details regarding the used resources are provided below.

**Electronic Databases:** ACM Digital Library and Science Direct and Business Source Complete. Scientific Journals: Journal of Organizational Design, Journal of Decision Systems, Software: Practice and Experience, Strategy & Leadership Journal, Business & Information Systems Engineering Journal, Journal of Big Data and Harvard Business Review.

**Others:** Technical Reports published by well-known companies such as IBM, McKinsey and Capgemini.

Regarding the automatic searches, the search was done by covering the meta-data in the case of the Business Complete Source, a very comprehensive scientific database in business, and full-text collection (meta-data and text) of the literature in the case of both ACM Digital Library and Science Direct. For electronic databases that index different areas of knowledge such as Science Direct, only results within the fields of Computer, Business, Management and Account, and Decision Sciences were taken into account.

## 2.4 Selection Criteria

This section describes the inclusion and exclusion criteria, the selection process as well as the quality assessment process used to guarantee that only relevant and significant literature results were accepted for analysis in the SLR.

### 2.4.1 Inclusion Criteria

(IC1) Studies should be published between January 2005 and February 2016 as big data may not have been known much earlier than 2005.

(IC2) Studies must be available in full version.

(IC3) Studies must be written in English.

(IC4) For duplicated works, the most complete one was selected.

(IC5) Research was related to Big Data in a managerial context (the focus of this SLR).

### 2.4.2 Exclusion Criteria

(EC1) The papers that did not meet the inclusion criteria were excluded.

(EC2) Books, dissertations and theses (in part, because of time constraints in going through this voluminous literature and, in part, some of this work would be expected in research publication form).

### 2.4.3 The Selection Process

The selection process is comprised of five steps adapted from Biochini et al., (2005) and Kitchenham and Charters (2007).

Step 1 - An automatic search was performed. The results were initially assessed by their title and abstract. The studies considered relevant to the context of the research were selected and the first list of selected studies was created.

Step 2 - A manual search was performed in business and management journals as well as conferences proceedings. The results were initially assessed by their title and abstract. The studies considered relevant to the context of the research were selected and the second list of selected studies was created. As commented by Kitchenham and Charters (2007), initial electronic searches result in a large number of irrelevant papers. Following this, the irrelevant results were excluded from further analysis.

Step 3 - In this phase the two lists were merged into a single one.

Step 4 - In this step the selected studies were assessed by reading their introduction and conclusion sections. The studies considered relevant to the context of the research were potentially selected for the next step. At the end of this phase, a fourth list of results was defined.

Step 5 - The last step enhanced the selection, mainly because the studies were completely read, analysed, and criticized in view of the contextual relevance and filter provided by the previous steps. In this phase the quality assessment process was applied and then a final list with selected results was created.

## 2.5 Data Extraction

In order to better organize the selected papers included into the SLR, a template composed of the following attributes was used: study id, title, authors, source, year of publication, full reference and the designated questions they address as well as important statements to help to answer the defined questions.

## 2.6 Quality Assessment

According to Kitchenham and Charters (2007), in addition to the general inclusion and exclusion criteria, it is usually considered important to assess the quality of the primary studies. Kitchenham also states that the quality assessment is important: i) to provide more detailed inclusion/exclusion criteria, ii) to guide the interpretation of findings iii) to determine

the strength of inferences and iv) to guide recommendations for further research.

For this study, the following quality assessment questions were defined:

(QA1): Are the aims of the research clearly stated?

(QA2): Are the research results and applications described in detail?

(QA3): Does the paper deal with the use of Big Data Analytics in decision making?

Based on the quality assessment, only papers that addressed the quality assessment questions and at least one of the research questions defined in this study were selected to be used into this SLR.

## 2.7 Descriptive Data and Analysis

During the first step (automatic search) a total of 1652 results were identified. After applying the inclusion and exclusion criteria and reading the title and abstract, only 50 studies were considered relevant. Moreover, a total number of 23 papers were selected during the second step (manual search) based on the inclusion and exclusion criteria as well. A third list was defined by merging the results from the two previous lists, totalling 73 papers.

After reading the introduction and conclusion of each article, 49 were considered relevant and selected for the next step, which consist of reading the full paper and applying the quality assessment process. No scoring method was used in this step.

The studies that did not meet the quality assessment criteria and did not address at least one of the research questions defined were excluded from this review (29 out of 49). Furthermore, the excluded studies addressed points not related to the main goal of this SLR (see section 1). These points included: (i) analytics techniques and algorithms, (ii) analytics framework, (iii) implementation of tools for value discovery, (iv) business intelligence and analytics, (v) process for starting to use Big Data in companies, and (vi) issues and policies for using Big Data Analytics in government, to name a few.

At the end of the selection process, 20 papers were considered relevant and selected for this SLR. There were 11 studies (55%) published in scientific journals, 4 (20%) published in conference proceedings and 5 (25%) white papers published by well-known companies. Approximately, 25% (5 studies) pointed out information to answer RQ1. 45% (9 studies) covered RQ2. The RQ3 was addressed by 25% (5 studies) and finally, the majority, around 65% (13 studies) of the papers addressed RQ4.

Table 1 presents the distribution of the studies in terms of the questions they address. The numerical

distribution of papers by research question can be seen in Fig. 1. The distribution of studies by year of publication is shown in Table 2. As can be clearly seen from this table, the Big Data centric results (pertaining to the focus of this SLR) appears to surface in the literature around 2011 when this research area began to gain traction in the community.

Table 1: Selected Primary Studies.

ID	Authors	Addressed RQ
S1	Kościelniak and Puto (2015).	RQ4
S2	Henry and Venkatraman (215)	RQ3
S3	Phillips-Wren and Hoskisson (2015)	RQ2, Q4
S4	Fan <i>et al</i> (2015)	RQ2, Q4
S5	Xu <i>et al</i> (2015)	RQ2
S6	Way and See (2015)	RQ3, Q4
S7	Ziora (2015)	RQ2, Q3
S8	Brown-Liburd <i>et al.</i> , (2015)	RQ2, Q4
S9	Colas <i>et al</i> (2014)	RQ4
S10	Schermann <i>et al.</i> , (2014)	RQ4
S11	Galbraith (2014)	RQ1, RQ2, RQ4
S12	Davenport (2014)	RQ1
S13	Luki� (2014)	RQ1, RQ3, RQ4
S14	Economist Intelligent unit (2013)	RQ2, RQ4
S15	Probst <i>et al</i> (2013)	RQ1
S16	Davenport (2013)	RQ1, Q2
S17	McAfee <i>et al.</i> , (2012)	RQ4
S18	Capgemini (2012)	RQ4
S19	McKinsey(2011)	RQ3
S20	Lavalle <i>et al.</i> , (2011)	RQ2, Q4

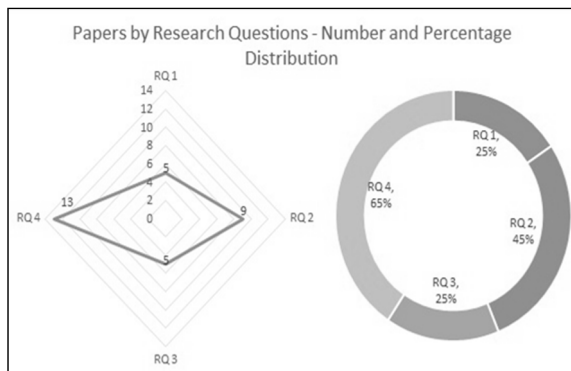


Figure 1: Numerical Distribution of Papers by Research Question.

Table 2: Number of Studies by Year.

Year	2011	2012	2013	2014	2015
Number of Papers	2	2	3	5	8

### 3 RESULTS AND DISCUSSION

This section discusses the results obtained for each research question defined in section 2, subsection 2.2.

#### 3.1 RQ1: How Are the Results of Big Data Analytics Used by Management in Corporate Decision-making?

The SLR analysis demonstrated that despite the recognition of the need to use and understand Big Data in corporate decisions (Capgemini, 2012), there has been little scientific research (5 papers since 2013) aimed at understanding how to use the analytics results in the decision-making process of organizations. Fourteen of 20 identified papers address the advantages and benefits of using Big Data Analytics to support decision-making, but not on an understanding on how to use the results in decision-making.

Galbraith (2014) states that the analytics results, during the analysis phase, should be done in real-time by fast-response teams. This can affect decision-making. He suggests that the analytics results should be used such that the team has to discuss the insights and decide on responses based on real-time action. However, an important factor to consider is how to organize these activities so as to facilitate real time decision-making. One recommendation is that companies should have multi-functional teams that are in constant contact with the data generated from different sources to respond to real-time inputs. The data from these different sources are then processed by analytics tools and the results used to make real-time decisions. This process allows companies to influence the outcome and prevent bad outcomes before they happen.

As an example on how big data analytics facilitates real-time decisions in managing supply chains is provided by Galbraith (2014): “At company A, there are specially designed rooms with video screens on the walls and computer access to various databases. The rooms are designed to foster real-time, cross-functional decision making. So when a paper machine’s embedded sensors at the Pampers’ plant in

a specific location indicate that it requires maintenance, a plant shutdown is scheduled. If it looks like the machine will be down for a while, then the decision is made to supply company A from the Albany, Georgia plant. The analytics capabilities are used to determine the best way to reroute trucks and still meet other delivery commitments to customers.

In the study conducted by Probst (2013), within various information technology companies that develop analytics tools, an important aspect on how to deal with the analytics results were pointed out: analyse the data and generate fast and intuitive reports, the called user friendly reports, which aims to empower the decision-making and provide companies with competitive advantages. The availability of easy to read reports can help companies to improve their decision-making capability as it contributes with clear and important information making it easier for the decision-maker to understand.

Davenport (2013) presents a 6-step approach to decision making in the context of Big Data. The steps are:

1. Problem Recognition;
2. Review Previous Findings;
3. Model the solution and select the variables;
4. Collect the data;
5. Analyse the data; and
6. Present and act on the results.

In this approach, for qualitative decision-making, the focus is on the first, second and last steps of the process which consist of: (1) frame the problem, identify it and (2) understand how others might have solved it in the past and (6) present the Analytics results and act on the results. The intermediate steps focus on (3) modelling the solution, (4) collecting the data and (5) analysing it.

For qualitative decision-making, following the 6 steps in order is important making necessary to formulate detailed hypotheses, get primary and secondary data on the hypothesized variables and finally run statistical models to check the usefulness of the data. Given the size of the big data, in his approach, the Big Data Analytics results are used in a way where they tell a story to decision makers and stakeholders, and based on that story, the decision will be made and actions will be taken upon it. In this approach the judgement and expertise of the decision-maker are also important as they are used for final decision.

In order to use the results of the Big Data Analytics in decision making, P&G (described by Colas et al., 2014) developed an initiative called

“Decisions Cockpits” which can be defined as dashboards that provide executives with visual displays of information on business performance and market trends. The idea is to provide a single source of truth for the information across geographies and business units. They can be customized and provide real-time automated information notifications. In this way, Big Data Analytics results helps to speed up decision making and reduce time to market (Colas et al., 2014).

### 3.2 RQ2: In Which Business Functions Are the Big Data Analytics Results Used?

In general, any business function can potentially use Big Data Analytics to make informed decisions. Examples are scattered in the literature. We identify nine business functions in this SLR, and add examples for each function in terms of how Big Data Analytics can be used in decision-making.

**Supply Chain** (Lavalle et al., 2011; Phillips-Wren and Hoskisson, 2015). In supply chain, companies use big data to describe the efficiency of its supply chain as well as to measure and monitor supply chain risks making decisions about location, product, etc. Questions such as What quality control measures will be used? Can be easily addressed by using Big Data Analytics.

**Product Research and Development** (Lavalle et al., 2011; Xu et al., 2015; Ziora, 2015). Companies can use Big Data to make new product decisions; Speed up the product development process: e.g., How can we improve the product design? What features should the product have to meet the customer's preferences?

**Marketing Management** (Davenport, 2013; Galbraith, 2014; Phillips-Wren and Hoskisson, 2015). Marketing Decisions such as customer opinions toward a product, service or company and marketing promotions: e.g., how to define the product marketing strategies? Where and when to release the product? What kind of visual aids should we use in a product campaign?

**Sales and Productivity** (Lavalle et al., 2011; Economist Intelligence Unit, 2013; Davenport, 2013). Optimize sales resource assignments, define sales strategy: e.g., Do our current sales staff need training to increase sales? How effective is our current sales strategy? What can we do to improve our current sales strategy? How much should we invest in training? Is there a way to lower that cost with a more effective strategy?

**Operations/Manufacturing** (Lavalle et al., 2011; Economist Intelligence Unit, 2013). Understanding variances that might be indicators of quality issues. Decisions might include: e.g., How to automate our operations? How to define future strategy to enhance our day-to-day operation?

**Human resources** (Economist Intelligence Unit, 2013; Ziora, 2015). Identify characteristics of most successful employees. Using predictive modelling to understand the workforce. The decisions involve improvements in the hiring and retention process. The use of cross-functional information combined promotion process, etc. Decisions involve process improvements, which personal to hire, retain and fire with the data in the human resources sector can be used to create a bigger context. This can be used to evaluate employees' performance.

**Risk Management** (Lavalle et al., 2011). Have an understanding of market risk, credit risk and operational risk: e.g., what are the vulnerabilities of our business? What actions should we take in order to reduce the risks?

**Investment Decisions/Financial Management** (The Economist, 2013). Have a better insight on how to spend money and how to borrow money: e.g., which investment strategy to use in? What can we do to best allocate capital to maximize its value? How much to borrow?

**Audit** (Brown-Liburd and Lombardi, 2015). Improving the efficiency of the audit procedures such as analyse external data in the assessment of client business risk, fraud risk, internal control.

Intuitively, it appears that practice is taking hold more widely in terms of diversity of business functions where Big Data Analytics results are being used to make decisions than what might appear from the SLR findings. Further empirical studies are clearly needed to uncover more facts.

### 3.3 RQ3: Which Aspects of the Decision-making Process Can Be Affected by Big Data Analytics?

In traditional decision-making processes, decisions involved human agents' skills, experience and judgement. In the Big Data context, operational decisions are partly or wholly replaced by automated algorithms as data-driven analysis is used instead of intuition (Way and See, 2015; Henry and Venkatraman, 2015).

This implies that any of the steps of a human decision-making process (such as: Identify the problem, gather the information, analyse the situation, develop and evaluate alternatives, select the

preferred alternative and action upon the problem) are eliminated or changed in some way, possibly introducing new steps for the human agent. In this context, Henry and Venkatraman (2015) state that there is less reliance on subjective managerial inputs due to the availability of real time insights from big data in order to make quality data-driven decisions.

Finally, the effort, time and cost involved in making a decision as well as to implement it may be affected by the use of Big Data Analytics (Ziora, 2015).

### 3.4 RQ4: What Are the Impediments to using Big Data Analytics Results for Effective Decision-making?

While Big Data Analytics offers many advantages and benefits to the users, it also brings challenges. In a Big Data Analytics context, companies face several impediments, both at the managerial and technical levels. At the technical level, the Big Data paradigm imposes numerous challenges due to possibly inconsistent and unstructured data (The Economist, 2013 and Madhavji et al., 2015) for which tools are still in the infancy (Capgemini, 2012).

At the management level, any organizational silos can make the decision-making suboptimal if data is not pooled together, across the silos, for the benefit of the organization at large. Of course, silos are an impediment to efficiently and effectively moving data and information across the organisation contributing to the potential for inconsistent reporting among the possibly geographically distributed business divisions (Capgemini, 2012). The silos can also lead companies to the issue of not having timely or relevant data across the business functions for effective decision-making.

A study conducted by MIT's Sloan School of Business shows that companies that engage in data-driven decision-making see a 5 to 6% increase in output and productivity over the ones that do not (Economist Intelligence Unit, 2013). However, the difficulty in aligning data-driven decision-making with the business strategy (McAfee et al., 2012; Phillips-Wren and Hoskisson, 2015) is considered as one of the most common problems companies face in the Big Data Analytics era as it requires an organizational culture change that involves intellectual, technological and social alignment.

Also, leveraging Big Bata often means working across functions such as IT, engineering, and finance, for instance (Colas et al., 2014). However, where cross-functional processes are of low maturity, organisations are not able to take advantage of the

Table 3: Impediments in using Big Data Analytics Results in corporations.

<i>Decision-Making Related Impediments</i>	<i>References</i>
<ul style="list-style-type: none"> <li>▪ Aligning data-driven decision-making with business strategy and development of the analytics strategy;</li> <li>▪ Leadership of Analytics initiatives;</li> <li>▪ Absence of clear business goals;</li> <li>▪ Managerial behaviour/Culture (Resistance to change within the organization)</li> <li>▪ Talent Management;</li> <li>▪ Organizational Silos;</li> <li>▪ Timely or relevant data across the company;</li> <li>▪ Cost of specific tools;</li> <li>▪ Centralization or Decentralization tendencies;</li> <li>▪ Inconsistent reporting of information among business units, geographies and functional operations;</li> <li>▪ Difficulty in integrate their own data sources within the organization;</li> <li>▪ Speed decision-making; and</li> <li>▪ Time to analyse the datasets.</li> </ul>	<p>Kościelniak and Puto (2015);  Phillips-Wren and Hoskisson (2015);  Fan et al., (2015);  Way and See (2015);  Brown-Liburd et al., (2015);  Colas et al (2014);  Schermann et al., (2014);  Galbraith (2014);  Li (2014);  Economist Intelligent unit (2013);  McAfee et al (2012);  Cappgemini (2012);  McKinsey(2011);  Lavalle et al., (2011)</p>

power of Big Data. Table 3 lists the impediments to using the results of Big Data Analytics in corporations.

#### 4 LIMITATIONS AND THREATS

We first discuss some limitations of this SLR study, followed by some threats to validity.

One obvious limitation is that the intersection of Big Data and corporate decisions is a relatively new topic, with much focus on Big Data currently being on data analytics. Thus, the difficulty in finding timely and relevant studies could be considered a limitation. Also, not all the electronic databases offer the same kinds of features to use the defined search strings. Thus, the search strings needed slight adjustments so that they could be used successfully.

Concerning the threats to validity, some threats were considered when analysing the results of the SLR.

**Construct Validity:** Regarding the search string used in this SLR (see subsection 2.3, sub-subsection 2.3.1), we used the terms considered most suitable in order to make the string as comprehensive as possible to capture the most relevant literature. We performed various tests using the identified terms and, approximately, five versions of the search string were generated in order to decide upon the final version. Thus, this threat was reasonably contained.

**Conclusion Validity:** All the conclusions drawn are shown to have been rooted in specific core sections of this paper – thus there is traceability. However, there can be an argument that data extraction from the selected papers could be biased. This was addressed in two ways. One is the use of two

researchers (primary and secondary), and making adjustments in interpretations as necessary. The second is the use of the data extraction form (see section 2, subsection 2.5) used to collect the information needed to be used into this SLR. The findings and outcomes of this study are based on consensus and organised data.

**Internal Validity:** Specifically, the selection process (see section 2, subsection 2.4, sub-subsection 2.4.3) in this SLR was conducted by two researchers simultaneously and any possible disagreement was discussed to reach a consensus from both researchers. By doing this, we tried to minimise any threats to internal validity. Regarding the manual search, it is important to note that it was performed only in a limited set of sources (e.g., magazines, journals, etc.). The rest of the data sources were searched using automatic search functions.

**External Validity:** This threat relates to whether the findings are applicable in contexts other than those presented in the study. An SLR study is not like a case study or a scientific experiment where this threat is of core importance because there are environment scopes (e.g., projects) outside the conducted study where one may wish to apply the case study or experiment results. Since the scope of the data (selected papers) in the SLR study is the universe to be considered, this threat is not considered relevant here.

However, despite care and collaborative effort, it is difficult to guarantee that all relevant published works and concepts related to the topic were included into this SLR.



## 5 CONCLUSIONS

A systematic literature was conducted in order to answer four research questions (RQ1-RQ4 – see Section 2.2) in the intersection between Big Data Analytics and decision-making process of enterprises. This topic is relatively new and, to our knowledge, no prior SLR studies on this topic have been conducted. The selection process for choosing the studies for analysis is composed of five steps (see section 2.4). After applying the inclusion and exclusion criteria, as well as the quality assessment process, twenty studies were considered relevant and selected to be used into this SLR (see Section 2/Table 1 for the list of studies selected).

This SLR study yields four main contributions: (1) presentation of the state-of-the-art on the intersection between Big Data Analytics and decision-making process (see section 3, subsections 3.1 to 3.4); (2) the understanding on how the Big Data Analytics results can contribute to the decision-making process (see section 3, subsection 3.1); (3) the identification of the business functions where Big Data Analytics has been applied (see section 3, subsection 3.2); and (4) the list of impediments for using the analytics in decision-making (see section 3, subsection 3.4 - Table 2). Collectively, these contributions add to the emerging knowledge base on Big Data Analytics and decision-making. Based on this SLR study, we conclude that Big Data Analytics results plays an important, multi-faceted, role in corporate decision-making.

On the management front, two important issues identified are: (i) aligning data-driven decision-making with business strategy and (ii) collaboration across business functions (See Section 3, subsection 3.4). Also, on the technical front, big data present some challenges due to lack of tools to process multiple properties of Big Data (such as variety, veracity, volume, and velocity).

Finally, the SLR results also demonstrates that there has been little scientific research aimed at understanding how to use the analytics results in the decision-making process of organizations. Most of the relevant studies address the advantages and benefits of using big data analytics to support the decision-making process. However, an understanding on how to use the results to make better decisions is still in its infancy.

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