Unlocking the full potential of Big Data

A change management approach

by

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Abstract

Big Data has experienced recent developments in the field of Business Intelligence and has captured the increasing interest of enterprises who are trying to seize its potential. More and more companies, operating in industries ranging from insurance to the entertainment industry, are moving forward with the adoption of Big Data, in an attempt to gain significant benefits, such as customer insight, increased value, faster decision-making, and the ability to maintain competitive advantage. Although a few companies, such as Amazon, Google, IBM and Netflix, have managed to reap the benefits from Big Data, most firms are in the very early stages of addressing the challenges presented by this new phenomenon and they still struggle to adapt to the changes that are required by Big Data.

This research aims to apply the theories of change management on the concept of Big Data, in order to develop a strategic model, which can later be used by companies to implement changes that may help in unlocking the full potential of Big Data. For that purpose, a mixed methods approach was chosen and the data was collected through the use of a questionnaire and interviews conducted worldwide with managers, consultants and experts in the field.

The final findings indicate that changes in both corporate resources and culture are necessary. In particular, corporate culture should favor close collaboration and knowledge exchange between data specialists and decision-makers. That is, leaders should encourage this change, and soft skills such us communication, teamwork and problem-solving should be pursued. At the same time, decision-makers should change their mindset, shifting from a decision-making process based on their "gut feeling" to a data-driven approach. The resulting resistance to change can originate from decision-makers mainly due to lack of information about the reasons of the change and from other employees, due to fear of not having the skills required. Moreover, companies where Big Data brings episodic changes are more likely to encounter resistance than others. In order to maximize the benefits of the change, companies should work to prevent and overcome specific instances of resistance by means of education and communication, initiatives for decision-makers and facilitation and support for all employees.

Keywords: Big Data, Business Intelligence, Management, Change Management, Resistance to change

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1 Introduction

Big Data has experienced recent developments in the field of Business Intelligence that has captured the increasing interest of enterprises trying to seize its potential. More and more companies, operating in industries ranging from insurance to the entertainment industry, are moving forward with the adoption of Big Data, in an attempt to gain significant benefits, such as customer insight, increased value, faster decision-making, in order to stay ahead of their competition. A recent study has shown that 73% of companies are already investing more than 20% of their overall technology budget on Big Data analytics, while 74% of enterprises admit that their main competitors are already using Big Data analytics to successfully differentiate their competitive strengths with clients, the media, and investors (Columbus, 2014). These numbers clearly indicate the important role that Big Data has to come play in the current business world and that companies are aware of this.

A few companies have managed to reap the benefits from Big Data and tremendously increase their profits. Netflix, a provider of on-demand Internet streaming media, collects and analyzes data from its 50 million subscribers around the world in order to understand and predict their viewing behavior. Additionally, Amazon uses Big Data for its product recommendation systems, while Google provides data analytics services. However, most of the other firms are in the very early stages of addressing the challenges presented by this new phenomenon and they still struggle to adapt to the changes that are required by Big Data. In order to understand how companies should respond, this paper explores the challenges that the introduction of Big Data brings inside a company, through the change management perspective.

1.1 Background

The appearance of the term Big Data was firstly introduced in an article during 1970, however, the number of research articles about Big Data experienced high growth from 2008 to the present "as the topic gained much attention over the last few years" (Halevi & Moed, 2012).

In general, *Big Data* refers to information assets that are high in volume, velocity and variety, thus demanding cost-effective and high performance computational platforms in order to be analyzed. Although, it has been researched broadly by the academic community, the vast majority of the academic literature refers to its technical or technological aspects. Little research has been conducted regarding how the change management theories apply to changes brought by the introduction of Big Data (Beyer & Laney, 2012). In its broad sense, *change management* refers to the process of managing change as a set of activities aimed at supporting any kind of change within a company (Paton & McCalman, 2008). One of the most influential studies on this topic is presented by McAfee & Brynjolfsson (2012), who describe Big Data as a “management revolution”. Their research suggests that Big Data is not merely a matter of using the right tools or technical skills but it also involves implementing managerial and cultural changes, towards embracing a more data-driven decision-making process. However, a gap on applying the change management theories for the implementation of such changes is observed and thus, further empirical research is required, in order to provide insight on how companies should proceed with these recommendations.

1.2 Aim and Objectives

This research aims to explore which strategies are the best approach for companies to deal with organizational changes that the introduction of Big Data requires. One of the major challenges of applying organizational change is the natural tendency of people to resist to that change, thus emphasis is placed on the human factor that affects the implementation phase of the changing process. We also aim to explore the source and causes of the resistance, as well as how the nature of the resistance can affect the success of the strategies. In order to examine the topic in more depth, three main questions were raised:

(i) What changes are necessary to reach the full potential of Big Data?
(ii) What kind of resistance can the company encounter?
(iii) How can the company overcome or prevent resistance?

These questions were set as the key objectives of this thesis, in the hope that would provide important information related to various concepts of this topic.

1.3 Research Purpose

The purpose of this research is to apply the theories of change management on the concept of Big Data, in order to develop a strategic model, which can later be used by other companies for implementing changes that will unlock the full potential of Big Data. We attempt to include a detailed description of these changes, and the way in which they affect the various organizational aspects of the company, such as decision-making, corporate culture, leadership etc., as well as the best ways to proceed with their implementation, in order to prevent or overcome resistance. The effectiveness of the model will be based on empirical research conducted on the current strategies of companies who are already using Big Data.

1.4 Research Limitations

This research is mainly constrained by the rather short duration of time, since the appearance of Big Data as a concept. It is a rather newly explored phenomenon and little research has been conducted regarding on how Big Data affects a company, from a managerial point view. Such a complex phenomenon requires an in depth and multifaceted approach and as the sources for our research were limited, finding related studying material from previous literature has been very challenging.

1.5 Outline of the Thesis

The rest of the thesis is divided into four main sections.

In Chapter 2, a critical description of the relevant literature review is presented, regarding the concepts of Big Data and the relevant theories of change management.

In Chapter 3, the methods of inquiry used to conduct the empirical research are described. The data collection and analysis process of the mixed methods approach that were used are presented in depth, followed by a description of the methods' validity and reliability.

In Chapter 4, the results of the research are analyzed and elaborated based on the concepts presented in the literature review.

Finally, Chapter 5 discusses the final findings, which are presented in comparison to the initial aims and objectives of this study. Practical implications and future research are also explored.

2 Literature/Theoretical Review

This section reviews important concepts of Big Data, and highlights the gap in the research of change management. Despite the recent interest in ‘Big Data’, due to its high operational and strategic potential, little is known about what encompasses the concept (Fosso Wamba, Akter, Edwards, Chopin & Gnanzou, 2015). Companies who want to adapt to Big Data encounter difficulties to even understand the concept of Big Data, thus many of them fail to recognize its importance in value creation and its contribution to the internal decision-making processes. There is a lack of both academic and empirical studies on the necessity of organizational changes that should be implemented in order to use Big Data to its full potential within their institution. In the next chapter, we attempt to bridge the existing knowledge gap in the literature; our aim is to describe the main concepts of Big Data and change management.

2.1 Introduction to Big Data

Many researchers have emphasized the importance of Big Data and the benefits it can bring to organizations. Big Data has high potential in creating competitive advantage and generating business value by “transforming processes, altering corporate ecosystems, and facilitating innovation” (Brown, Chul, & Manyika, 2012). Gehrke (2012) suggested that it can facilitate companies to respond to various businesses challenges, while Davenport, Barth & Bean (2012) argue that it has the potential to offer insights and help unleash “new organizational capabilities”.

2.1.1 The definition of Big Data

Big Data is a relatively young concept which is growing quickly and disorderly, thus still, no universally accepted definition exists (De Mauro, Greco and Grimaldi, 2015). By means of a detailed survey of existing definitions of this concept, De Mauro et al. (2015) concluded that “Big Data represents the Information assets characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value” (De Mauro et al., 2015, p. 8). A similar definition is given by the National Institute of Standards and Technology (2014), which informs that “Big Data consists of extensive datasets, primarily in the characteristics of volume, velocity, and/or variety that require a scalable architecture for efficient storage, manipulation, and analysis" (NIST, 2014, p.5). A popular definition is the one proposed by Beyer & Laney (2012), two analysts of the IT research company Gartner: "Big data is high-volume, -velocity and -variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making".

The three V's (Volume, velocity and variety) appear to be the universally recognized characteristics of Big Data (Laney, 2001; Suthaharan, 2014; McAfee & Brynjolfsson, 2012), however other authors and practitioners add "value" (Dijcks, 2012), complexity (Kwon, Lee & Shin, 2014; SAS Institute Inc.), "veracity" (Siewert, 2013), "variability" (SAS Institute Inc.), "consilience" and "granularity" (George, Haas & Pentland, 2014).

A different view suggests that Big Data is not a new concept but rather a Buzzword for the already existing data analytics applied on much larger data sets. A few IT vendors and solutions providers use Big Data in the context of being "a smarter, more insightful data analysis" (Davenport et al., 2012, p.43). Indeed, companies have been familiar with processing extremely large data sets for decades, in order to gain insight about their customers and improve their decision-making. However, Davenport et al. (2012) argues that: "companies (...) will use real-time information from [various] identifying devices to understand their business environments at a more granular level, to create new products and services, and to respond to changes in usage patterns as they occur" (Davenport et al., 2012, p.43). Although, it could be argued that Big Data is an extension of Business Intelligence, Big Data requires new tools and technology in order to overcome the challenges that derives from the large volume and unstructured nature of the data.

2.1.2 Sources of Big Data

Big data comes from an enormous plurality of sources; Internet clicks, posts to social media sites, mobile transactions, digital pictures and videos, sensors for climate information, sale and purchase transaction records and cell phone GPS signals are just few examples.

George et al. (2014) summarize all these sources in five categories: public, private, exhaust, community and self-quantification. Public data is held by governments, governmental organizations, and local communities, while private data is possessed by individuals, private companies and nonprofit organizations. Data exhaust involves data passively generated by everyday actions, such as Internet searches and several other online activities. Finally, community and self-quantification data is the information that can be gathered respectively on social networks and through analyzing individual and interactive behaviors.

2.1.3 Applications

Thanks to the increasingly faster technology development, it is now possible to generate value from Big Data in several different ways (Nunan & Di Domenico, 2013) by creating efficiencies, enabling new capabilities, and opening up previously unrealized opportunities (Fulgoni, 2013).

Big Data is therefore bringing changes to many industries, such as the transportation sector (Tanaka, 2015), sciences (Honavar, 2014; Mitra-Thakur, 2014), the public sector (Fasel, 2014), book publishing industry (Lichtenberg, 2014), and healthcare (Curtis, Brown & Platt, 2014; Hamilton, 2013). Big Data can also add value to several business functions, such as supply chain management (Schoenherr & Speier-Pero, 2015), marketing and CRM (Fulgoni, 2013; Phillips-Wren & Hoskisson, 2015). Capriotti (2014) explains how Big Data can improve the internal audit process of companies that decide to introduce Big Data into their accounting sector, thanks to "a more developed, mature, and sustainable (..) continuous risk assessment process" (Capriotti, 2014, p.2).

2.1.4 Challenges

The use of Big Data can offer many benefits, however, there are also several challenges that need to be addressed.
First of all, as a new technology, Big Data offers several technical and technological challenges. Due to its massive volume (from terabytes to exabytes), complexity and unstructured nature, it requires advanced data storage, extremely high computational performance, as well as analysis and visualization techniques (Chen, Chiang & Storey, 2012; De Mauro et al., 2015). In order to analyze Big Data, George et al. (2014) explain that familiar statistical approaches cannot be applied and therefore, analysts should explore new methods and techniques. Additionally, other important challenges include data acquisition, reduction, integration, visualization, benchmarking etc. as well as data privacy and ownership issues (Jagadish, Gehrke, Labrinidis, Papakonstantinou, Patel, Ramakrishnan & Shahabi, 2014).

Another challenge concerns data privacy. A huge amount of data is now available for collection, however, this free use of consumers' data can have privacy implications. Pentland, in his interview by Berinato (2014), explains that the collection of personal data can be very powerful but it can also be easily abused. He affirms that companies do not own the data, and that, without rules defining data ownership regulations, consumers can slow down the process and limit the result efficiency in data analysis.

Furthermore, working with Big Data requires the use of certain skills and abilities. It is rather obvious that statistical knowledge is important, although, knowledge on processing methods that go beyond the traditional statistical techniques should be acquired (De Mauro et al., 2015).

According to Power (2014), Big Data scientists should embed a number of skills, including those of database designers, software programmers, statisticians and storytellers. However, people that possess this kind of knowledge are “hard to find in today’s job marketplace” (De Mauro et al., 2015). Other scholars emphasize the need for knowledge and skills also outside the fields of statistics and IT. Chen et al. (2012) highlight the significance of business knowledge and effective communication skills, and they even propose “a new vision” for Information Systems programs with an interdisciplinary structure, covering analytical, IT, and business skills together.

An alternative perspective on the main challenges of Big Data was recently presented by Andrew McAfee and Erik Brynjolfsson in their article “Big Data: The Management Revolution” (2012). There, the authors list “five management challenges” that they think companies need to address, in order to gain the full benefits of Big Data. Among these, technological and talent management challenges (as also mentioned above) are included, however this paper also emphasizes the importance of leadership, decision making, and company culture. They explain that companies require leaders that know how to ”set clear goals, define what success looks like, and ask the right questions”, while having the ability to set a vision and persuade other to follow (McAfee & Brynjolfsson, 2012). Moreover, a company should embrace a culture, where the decision making process is more data-driven and less based on the manager’s intuition.

In conclusion, despite its challenges, it is clear that Big Data has the potential to bring tremendous benefits to a firm and thus, it can be seen as a game changer that brings new variables to the table. As McAfee and Brynjolfsson (2012) also argue, “companies won’t reap the full benefits of a transition to using big data unless they are able to manage change efficiently”. Consequently, an important question is raised: How should companies respond to these challenges in order to reach the full potential of Big Data?

In the search of an answer to such a complex question, we believe that more than a technical approach is required. In order to analyze the changes and find strategies to overcome the challenges of the introduction of Big Data, one should first examine in depth the various aspects of “change” and how it should be managed. In the following chapter, we present a critical literature review of the basic concepts of change management.

2.2 Change Management

Organizational change has been extensively researched since the 1950s (Bamford & Forrester, 2003) and currently the literature covering this topic is rich, rather thorough, and “highly responsive to the demands of management and also the workplace and market” (Paton & McCalman, 2008, p.3). However, since change management can be analyzed from several theoretical perspectives and disciplines, some studies include contradictory theories and research findings that are not empirically proved, or sustained by unchallenged hypotheses (By, 2005). Besides, Sveningsson & Sörgärde (2013) strongly argue that “no single perspective provides us with lasting answers to the many facets of organizational change”. In this research we analyze the nature of change based on the episodic and continuous views of change. The reason of this is because, as mentioned before, the appearance of Big Data is perceived by most as either a newly developed concept (episodic change) or as an extension of Business Intelligence (continuous change).

2.2.1 Definition of change management

A lack of a general agreement also exists regarding the definition of change management. Currently, as Kang (2015) argues, there is no single definition, because change management is a term that embraces a wide range of applications (Jansson, 2008 in Kang 2015).
Some authors use the term “change management” as the equivalent of “managing change”, which is the set of activities aimed at supporting any kind of change within a company (Paton & McCalman, 2008). On the other hand, more specific definitions are provided by both researchers and practitioners, who emphasize different aspects of change, such as processes, techniques, and the roles of change agents (Kang, 2015).
In an effort to clarify this issue, Kang (2015) divided the definitions of change management in two main categories, “Macro change management” and “Micro change management”, which differ from each other by the level of change, focus, and role, and the required competencies of the change agent. The first category includes definitions that refer to the change as an overall process and thus, considers change management as “synonymous with the intended process for systemic, transformational, and fundamental change” (Kang, 2015, p.27). According to Kang (2015), the scholars who propose this kind of definition are, in chronological order: Lewin (1951), with his influential three-step change model (described later in this chapter), Kotter & Cohen (2002), By (2005), and Hayes (2006).
The second category groups together tactics or guidelines to implement change effectively, that include also the human aspects involved in the change processes. An example of “Micro change management” definition is the one given by the practitioner Tim Creasey (2007), who defines change management as “the process, tools and techniques to manage the people-side of change to achieve the required business outcome” (Creasey, 2007, p.3).
In this research, we examine both the Macro and Micro perspective of change management.

2.2.2 Change: triggers and classifications

In order to respond to change, it is first important to identify the forces that lead to change and analyze its nature and characteristics.

In their book "Changing organizational culture" Alvesson and Sveningsson (2008) explain that change is the result of external and internal drivers, which tend to mix and overlap. The external forces that lead a company to change can be political, technological, cultural, demographic, economic, or related to the market where the organization operates (Child, 2005 in Alvesson & Sveningsson, 2008). On the other hand, the internal triggers can be related to management change, internal problems at work, high employee turnover, loss of key staff, new products or services, implementation of new technology, merger or acquisitions (Lientz & Rea, 2004).

Episodic and continuous change

One way to distinguish organizational change is to divide it into two comprehensive categories: episodic (discontinuous) and continuous change. Episodic change is infrequent and intermittent, usually triggered by external forces, thus organizations are perceived as balancing between long periods of stability and short eruptions of change (Weick & Quinn, 1999). This view is based on the assumption that change occurs in phases and that stability is the natural stage of organizations (Sveningsson & Sörgärde, 2013). However, this idea has received extensive criticism regarding its limited scope or usefulness (Pettigrew, 1985; Alvesson & Sveningsson, 2008). Change models connected to managing episodic changes tend to be synoptic and despite the fact that they enable managers to define an overall plan, they fail to indicate the changes between the stages of the plan. Additionally, Tsoukas & Chia (2002) support that "change is the normal condition of organizational life" (Tsoukas & Chia, 2002, p. 567), thus managers searching only for indications of episodic change initiated by external forces might miss the non-linear micro-processes that inhibit or drive change.

In contrast, continuous change refers to "organizational changes that tend to be ongoing, evolving, and cumulative" (Weick & Quinn, 1999, p.375). This type of change can be seen as a processual approach to change, also known as performative change, which is described as a continuous process rather than occasional disruption (Sveningsson & Sörgärde, 2013). A variety of day-to-day decisions and actions performed with the coordination of the organizational members can facilitate the change. These tasks are occasionally amplified, repeated and sustained over time and as a result they manage to produce major change (Orlikowski, 1996 in Sveningsson & Sörgärde, 2013).

Weick and Quinn (1999) point out that episodic and continuous are simply two different perspectives which depend on the level of analysis of the observer (i.e. distant or close). A macro-level of analysis (from distance) leads to an episodic view of the change, since "when observers examine the flow of events that constitute organizing, they see what looks like repetitive action, routine, and inertia dotted with occasional episodes of revolutionary change". On the other hand, from a micro-level analysis (closer) ongoing adaptation and adjustment, even if small, is visible, and therefore the observer has a continuous view of change.

Furthermore, other classifications of change presented in the literature include:

- first-order or second order (Watzlawick, Weakland & Fisch, 1974)
- revolutionary (transformational) or evolutionary (transactional) (Burke, 2002)
- incremental or radical change (Bateson, 1972)
- strategic or operational (Burke, 2002 in Alvesson & Sveningsson, 2008)
- total system or local option (Burke, 2002 in Alvesson & Sveningsson, 2008)

2.2.3 Organizational change process

Organizational change implementation can be categorized in three interrelated approaches: directed change, planned change and guided change process (Kerber & Buono, 2005).

Directed change

The directed change process follows a top-bottom approach, which derives from authority, persuasion and compliance (Kerber & Buono, 2007). The change process is initiated by managers or leaders, who are responsible for organizing and introducing the changes to the rest of the organizational members. This type of change is considered as a quick approach of implementing the change and it is the responsibility of the managers to establish the acceptance of the employees, based on "business necessity, logical arguments (rational persuasion), emotional appeals, and the leader's personal credibility" (Kerber & Buono, 2009).

Guided change

The guided change is a process based on the commitment and contributions of organizational members, with the aim of taking full advantage of their expertise and creativity. This is an iterative approach, because it includes an initial design which can be modified during the implementation (Kerber & Buono, 2007).

Planned change (Lewin)

Planned change may arise from any level in the organization although ultimately, it is sponsored by the top. It involves having a clear vision and specific goals, and the leadership is responsible for giving the direction while influencing how these goals will be reached (Leonard, 2013).

This approach is reflected in one of the most influential models of change management, the Lewis' three-step model (1951), which sees change from an episodic perspective and that divides the organizational change process in three phases: unfreezing, change, and refreezing.

The unfreezing step includes preparatory and planning activities, such as "projects, education or inspiring talk from significant persons" (Alvesson & Sveningsson, 2008) that aim to make the people involved in the change understand the reasons of it. The second step describes the time when the organization shifts to the new pattern, followed by the refreezing phase, where the change agents focus on stabilizing the new state and impeding it from returning to the initial one.

Sveningsson & Sörgärde (2013) explain that this approach depicts an organization as an entity influenced by forces of change and stabilization, where knowledge, commitment and learning are the tools that allow firms to limit resistance from employees. However, what exactly is resistance?

2.2.4 Resistance to change

Resistance to change is one of the main reasons why change programs can fail (Vaccarezza & Rizzi, 2014), and often results in decreased effectiveness and increased costs (Kotter & Schlesinger, 2008). It rises from "fear, prejudice, anxiety and ignorance" (Paton & McCalman, 2008) and can be active or passive, open or underground (Lientz & Rea, 2004). People resist to change because "they fear the unknown and are comforted by the familiar" and also because "very often successes and power bases are routed in the past and present, not necessarily in the future" (Paton & McCalman, 2008, p.52) and therefore it jeopardizes their position, control and reputation.

Change management literature provides us of several insights around the topic of resistance to change (Kotter, 1996; LaMarsh, 1995; Bruhn, Zajaz and Al-Kazemi, 2001; Oreg, 2003; Alvesson & Sveningsson, 2008; Paton & McCalman, 2008; Wiggins, 2009; Harvey & Broyles, 2010, and many others). Since it would be impossible to list all the available theories, we selected the Kotter and Schlesinger's perspective, which seems to summarize in few clear points most of all the existing approaches.

In their article published by Harvard Business Review, Kotter and Schlesinger (2008) explain that there are four main reasons for resistance:

- *parochial self-interest*, i.e. the desire not to lose something of value such as their position in the company
- *misunderstanding* of the change and its implications due to lack of information about the reasons of the change, and, therefore, *lack of trust* in the person who initiated the change
- *different assessments*, for example a belief that the change is not suitable for the company or that costs exceed the benefits. In other words, if employees are not committed to the change process
- *low tolerance for change*, such as fear of not being able to develop the new skills and behavior required

Moreover, Kotter and Schlesinger (2008) suggest some methods of dealing with resistance to change, yet depending on the causes of resistance. The authors recommend using:

- *education and communication*, such as discussions and group presentations
- *participation and involvement* of the resisters or potential resisters into the change process (design and/or implementation)
- *facilitation and support*, i.e. offering to the employees trainings in the new skills required, or simply providing emotional support to deal with the change

- *negotiation and agreement*, i.e. offering incentives such as higher wage or pension benefits
- *manipulation and cooptation*
- *explicit and implicit coercion*, i.e. forcing resisters to accept the change by threatening, firing or moving them to another office.

In addition, the authors explain that managers should use different approaches depending on the reason of resistance. We summarized the relationship between the strategies and the reasons of resistance in Table 2.1.

Table 2.1 Kotter and Schlesinger's strategies to prevent/overcome resistance

Strategy	**To apply in case of**
Education and communication	misunderstanding of the change and its implications
Participation and involvement	different assessments
Facilitation and support	low tolerance for change
Negotiation and agreement	parochial self-interest (especially when resisters are powerful individuals)
Manipulation and co-optation or explicit and implicit coercion	when the previous solutions do not give satisfying results

The Kotter and Schlesinger's model has been included in the survey and, in the analysis chapter, we examine if companies have applied it, in order to prevent or overcome resistance that accompanies the introduction of Big Data.

As concluded, the introduction of Big Data in a company requires fundamental change in different areas. However, currently there are no change management theories applied on Big Data, mentioned in any literature published by the academic community. Of course, a quite vast amount of practitioners' articles and reports can be found on the Web (for example in consultancy companies or analytics software vendors' websites), although they cannot be considered as valid or established knowledge, as these articles are highly likely to be biased by the true intentions of their authors (e.g. aiming to sell more Big Data services).

On the other hand, we considered McAfee and Brynjolfsson's article a valuable and inspiring starting point for our research. Consequently, the fundamental concepts of this study are based on the ideas and theories of management that these two authors apply on Big Data.

In the following chapter, the research approach and the design that was used is describe in detail.

3 Methodology

3.1 Research Approach and Design

The purpose of this research is to explore how the various theories of Change Management apply on the changes introduced by Big Data, and their effect on the process of unlocking its full potential. Initially, there was a lack of information from previous research, thus it was deemed necessary to gather new data. In order to explore the study questions in-depth, a primary research with a mixed method approach was selected (Tashakkori & Teddlie, 2003). According to Creswell (2002) this design focuses on collecting, analyzing, and mixing both quantitative and qualitative data in a single study, the combination of which aims to provide a better understanding of research problems than either approach alone. The purpose of this study requires exploring a rather complex issue, thus, using a single type of research would be limiting. In order to examine the selected topic investigate, both methods were used to complement each other, thus providing more comprehensive results (Green, Caracelli & Graham, 1989).

Following the mixed method strategy of inquiry, a sequential procedure was conducted. The implementation consisted of two chronologically distinct phases. Initially, a web-based survey (questionnaire) was developed, to collect as much data as possible (quantitative method); indeed, surveys can be easily administered online to many participants. Additionally, respondents find questionnaires because they appear to be quicker and easy to complete (Dillman, 1978; Goyder, 1988), while they can complete the questionnaire in their own time. The survey questions were developed based on the theories of change management that were presented in the literature review, as well as our general concerns/problematization on the topic. In the second phase, and after having completed the questionnaire analysis, interviews were conducted (qualitative analysis). The objective was to get an in-depth view and to clarify or examine in detail certain aspects of the research that were not clearly answered in the first phase.

Each method had its own set of questions (see *survey questions* in Appendix A), however, all of them were developed under the same concept, so that the final results of both research methods would contribute into providing answers to our three main research concerns:

(i) What changes are necessary to reach the full potential of Big Data?
(ii) What kind of resistance can the company encounter?
(iii) How can the company prevent or overcome resistance?

3.2 Data Collection Method

In this chapter the two different methods that were used for the mixed methods approach are described separately and explained in detail.

3.2.1 Quantitative approach: Questionnaire

The objective of the quantitative research was to identify the potential predictive power of the selected variables of change that Big Data requires from the change management process, as well as gather quantitative data regarding the effectiveness of the changes that the participants have already implemented. The questionnaire was developed in Google Forms, a free web-based survey program offered by Google. It allows to create a personalized survey with easy distribution to participants, while their responses are saved into a spreadsheet.

The questionnaire was formed as a combination of close-ended and open-ended questions. Most of them were close-ended questions, which were used to provide the numerical data that were required for the statistical analysis; this type of questions were chosen because of their efficiency and ease of analysis (Seliger & Shohamy, 1989). Close-ended questions included Yes/No questions, multiple choice questions (both single-answer and multiple-answer) and scaling matrix questions. The Yes/No questions were mostly accompanied by an “I don’t know” choice to reduce missing data, which is a frequent problem of questionnaires (Bryman & Bell, 2007). The matrix questions allowed the respondents to only pick one column choice per row and their available answers were formed based on a 5-point Likert scale as following: 1. Not relevant, 2. Slightly relevant, 3. Moderately relevant, 4. Relevant, 5. Very relevant. The Likert scale was particularly helpful, since its flexible response system gave us the ability to investigate the intensity of the effect of each Likert item, based on the perception of the respondent. Additionally, as it is balanced on both sides of a neutral it was considered a less biased measurement (Bryman & Bell, 2007).
Furthermore, open-ended questions were considered of great importance, since, according to Gillham (2000, p. 5), they “can lead to a greater level of discovery”. The latter gave the possibility to the respondents to provide their own answers (i.e. other changes/ skills/causes etc.), which later on were used as additional information in the qualitative research. Moreover, the questionnaire included contingency questions (i.e. based on the answer given to the previous question), thus, avoiding asking questions that do not apply to certain participants (see survey flowchart in Appendix A).

In order to receive answers to these questions, there were several aspects that we had to take into consideration during the process of selecting our target group. Our first thought was to have a target group only consisted of managers, since they are the decision-makers in a company and thus they are responsible for implementing the changes. However, after consideration we saw that these answers would most likely present one side of the story, as managers have their own point-of-view on what changes are necessary, their success and how (or if) resistance was managed. Acquiring a more spherical view and probably more accurate findings presented the need of expanding our target group and involve a wider set people. Therefore, apart from managers, we also reached out to other groups of professionals, such as analysts, IT specialists and consultants.

Furthermore, we tried to minimize the dependence of the data to the geographical factors as much as possible by inviting people from all over the world to participate in the questionnaire. We saw this step as very important part of the research; as a new technology, Big Data requires several resources, such as expensive hardware/software tools and certain workforce skills/abilities, which can be a barrier to less developed countries, due to the high costs. Our effort was to minimize this kind of dependency, so our results remain unaffected by such a limitations.

The majority of the survey participants was found through “LinkedIn”, an online business-oriented social networking service. Initially, the survey was shared with around 60 “LinkedIn groups” that were related to Big Data. However, the response rate was very low, thus we individually contacted almost 350 people, whose LinkedIn profile proved their involvement in Big Data.
Eventually, 68 questionnaires were collected. Among these, 44 respondents stated that their company works with Big Data, 11 that the company does not, 9 that the introduction of Big Data is planned in the near future, and 4 that they do not know whether their company works with Big Data or not.

In the analysis presented in Chapter 4, only 44 of the participants that have stated that their company currently works with Big Data are considered.
Among them, 35 participants have stated that they work directly with Big Data (63% works for more than 3 years, 20% from 1 to 3 years and the rest for less than 1 year), 9 stated that they do not work directly with Big Data, however 6 of them state that their activity is influenced by it.
A 30% of the participants are CEOs or Top Managers, 36% are First-line or Middle managers and the rest of them are consultants, analysts and IT specialists. 34% of the sample is less than 31 years old, 57% is between 31 and 50 years old, and 31% is more than 50 years old.
The respondents’ companies are located worldwide (55% in Europe, 30% in North America, 15% in Oceania, South and Central America and South and East Asia) and have different company size (25% has less than 50 employees, 21% between 50 and 999, 23% between 1000 and 4999, and 30% more than 5000). They rely on Big Data mostly for activities related to customers (Customer and Market Analysis and/or Customer Service) and to Information Technology (respectively 48% and 43%), followed by the R&D department (32%).

3.2.2 Qualitative approach: Interviews

In the second phase, the qualitative multiple-case study approach was conducted through a series of semi-structured interviews, in order to collect empirical information directly from knowledgeable participants.

A total of seven interviewees were selected carefully among a list of volunteers, who, during the survey, indicated their availability to be interviewed. Four managers (including one CEO) were chosen, since as decision-makers, their role is of great significance in implementing the change and eliminating resistance, thus their insight was considered vital for this research. The rest of the interviewees were consultants because they can provide a complementary, more spherical view of how other companies deal with Big Data. In addition, having worked with numerous companies, they might have gained valuable expertise including the most efficient strategies for implementing organizational change for gaining the best results with Big Data. Apart from their job position, we tried to choose interviewees so that there was a variety in terms of their age (ranging from 25 to 65), location (Europe, Canada, Australia and the U.S.) and also the number of employees in the company. All of them declared that their company works with Big Data (either as an internal resource or as a service offered to their customers).

The interview was conducted in a person-to-person form and - depending on the location of the interviewee - it took place either in person or through internet-based calls (via the Skype application). Among the four main types of interview divided by Patton (1990), an interview guide approach was selected, which allowed us to cover all the desired topics in a systematic way but also allowed for a flexible conversation to develop. The atmosphere of the interview was formal but friendly, while the language that was used avoided the excessive use of academic or theoretical terms, with which practitioners could be unfamiliar. The beginning of the interview included a brief introduction to the topic and the purpose of the interview.

Prior to the interviews, two different sets of questions were created: the preliminary questions and the main questions. The preliminary questions helped us identify with the personal characteristics and attributes of the interviewees, which in turn allowed us to better understand their background. The main questions, were developed in an open-ended format and they were based on the three main questions that were presented at the start of this chapter. However, they were adjusted according to the findings of the first phase, in order to provide a more in-depth explanation of these statistical results by analyzing the interviewee’s perspective. Additionally, certain questions were adjusted based on the interviewees’ profile, i.e. job position. All the interviews lasted between 30 to 50 minutes, and all of them were in English, with an exception of an interview that was conducted in Italian, as it was the mother tongue of the interviewee.

3.3 Data Analysis

The use of a mixed methods approach required treating each data set differently, thus quantitative and qualitative techniques were used to analyze quantitative and qualitative data, respectively. However, the results of both of the analyses are finally combined to be used at the interpretive level of this research.

The analysis of the data collected by the online questionnaire was conducted in four main steps. The first step was conducted directly on the spreadsheet on all the variables, while the next ones were conducted by using SPSS, only on the variables that were relevant to the analysis:

1. *Data manipulation and coding:* all the ordinal and dichotomous variables were transformed into a numeric format and dummies were created for all the variables from questions that allowed for multiple answers. This procedure was chosen in order to facilitate the quantitative analysis (Bryman & Bell, 2007).
2. *Univariate Analysis:* Frequency tables and different types of charts (depending on the variable type) were created for every variable, in order to get an overview of the data. For the ordinal variables we calculated the measures of central tendency (arithmetic mean, median and mode) and the standard deviation.
3. *Bivariate Analysis:* In this step, the relationships between variables were analyzed, again with the use of SPSS. In particular, we applied:
    a) Cramer's V and Pearson chi-square for nominal variables. In particular, the Cramer's V measure of association was used for analyzing tables larger than 2 × 2, as suggested by Everitt and Skrondal (2010) in the Cambridge dictionary of statistics.
    b) Spearman´s rho, in order to analyze ordinal variables
    c) Fisher's exact test, which is suitable in this case, as it computes the "exact" (i.e. correct) p-value and is therefore particularly useful when the expected frequencies are small (Everitt and Skrondal, 2010).
    d) Gamma, in order to analyze dichotomous variables.
    e) Linear and Logistic regression, which predicts a binary outcome using one or more independent predictor(s).
    f) Linear-by-Linear Association in Chi-squares tests, "for detecting specific types of departure from independence in a contingency table in which both the row and column categories have a natural order" (Everitt and Skrondal, 2010, p. 252).
4. *Factor analysis***:** we used this procedure to group the list of changes we investigated into two different groups, each of which describes an aspect of the studied changes (Vogt, 2005).

For the qualitative research, a thematic analysis based on the three main questions was conducted and the themes created (changes, resistance, solutions to resistance) allowed us to combine and compare the results with those of the quantitative analysis. A coding technique (Bryman & Bell,

2007) was applied on the data, where various keywords were used (i.e. leadership, corporate culture, decision-making) to code the information based on the concepts used in the literature review. The "reading" of the data was repeated several times, since in many cases useful information was not discussed in a direct/apparent way. In addition, some of the concepts were discussed in the same sections of the interviews, thus separating under the set categories was not trivial. However, our technical and analytical skills (previously gained through working experience) combined with our business management knowledge were used for an intuitive extraction and analysis of information. Lastly, the qualitative research also involved a cross-case analysis, where relevant sections of different interviews were put together.

3.4 Validity and Reliability

The mixed methods approach provided a good solution for triangulation (Bryman & Bell, 2007), since it combined both quantitative and qualitative techniques in a complementary manner.

The questionnaire was first tested within a small fraction of the population, which provided useful feedback for further adjustments before the final release. Additionally, the randomized response method was used in various questions in an effort to overcome biases, possibly result from the order in which options are presented. Reliability is estimated in terms of internal consistency, by measuring the same concept with different questions. A correlation between those questions was then used, in order to determine reliability.

In order to establish the trustworthiness of qualitative research, purposive sampling was used prior to the interviews for selecting knowledgeable participants based upon their professional experience and their relevance to the questions posed (Bryman & Bell, 2007). As an additional step, we had included a general theoretical knowledge question concerning Big Data, to ensure that the interviewees had good knowledge on the topic. During the interview, informal member checks were carried out by utilizing techniques such as paraphrasing and summarization of the responses to check whether our understanding of the interviewees' perception was accurate (Lincoln & Guba, 1985). Transferability of the research was pursued by providing "thick" descriptions of the research findings in the analysis (Bryman & Bell, 2007; Lincoln & Guba, 1985). Additionally, the fact that the interviews were conducted by two individuals enhanced the confirmability of the internal coherence of the overall conduction and analysis process (Bryman & Bell, 2007).

Lastly, in both methods the participants were asked to add comments regarding the research as a way of receiving constructive feedback, thus, allowing the respondents to confirm or criticize the validity of the study.

3.5 Implications and limitations for research

Finding and reaching out to the appropriate participants, for both methods, was a challenge, since our target group was very specific (professionals that have experience with Big Data), and as students, we lacked the professional network required. Therefore, the sample in both methods was rather small, although it is also considered representative.
Furthermore, the concepts used are not strictly defined (i.e. definition of change, nature of change etc.) and they can be perceived in a different way by each individual. This leaves the interpretation open to both the participants and the study conductors, which might cause the appearance of biases. The purpose of the mixed methods approach also focused on neutralizing such biases by gaining insight into different levels of the analysis (Tashakkori & Teddlie, 1998).

In the following chapter the results of the analysis are described and explained in detail.

4 Analysis and Discussion

The analysis provided in this chapter has been divided thematically based on the three research objectives (see Chapter 1) as following: (i) the changes required with the introduction of Big Data, (ii) the resistance that companies can encounter, and (iii) the strategies companies should apply to prevent or overcome this resistance. Both quantitative and qualitative data are presented side-by-side in three different sections and the findings are discussed at the end of the chapter.

4.1 Changes required with the introduction of Big Data

In this section, the nature of change based on the participants' views (episodic/continuous) is examined, while later on, each change is analyzed separately but also all together as a group. Finally, we examine whether these changes were enough to unlock the full potential of Big Data, based on the participants' opinion.

The changes that have been used in the analysis are as following:

- Change in the decision-making process
- Change in leadership style
- Change in the corporate culture
- New data security policies and regulations
- New technologies
- New skills and abilities
- Technical changes (data collection, processing and analysis)

4.1.1 The different perspectives on the change

During the quantitative analysis, we tried to understand how participants perceived change in their company. To the question "Which of these statements best applies to how the change brought by Big Data is/was managed in your organization?", they were presented with different options to choose from, which are related to continuous or episodic change. As shown in Figure 4.1, 61% answered that Big Data caused an episodic change, 25% answered that the company is undergoing through continuous changes, while 14% of the participants thought that the company did not face any changes caused by the use of Big Data.

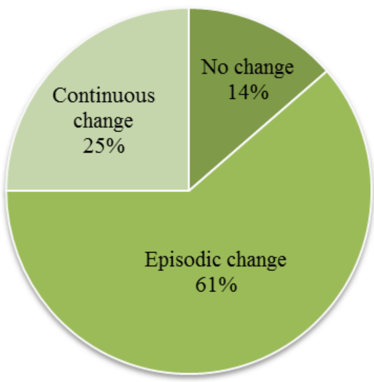

Figure 4.1 Percentage of different perspectives on change

In addition, we cross-tabulated the results of the aforementioned question with the responses to the question "Which of these statements best applies to how change is managed in general in your organization?" where the same changes were presented as possible responses. What we discovered is that these two variables have a moderate relationship; the measure of Cramer's V association was equal to 0.565, where 0 means "no relationship and 1 "perfect relationship" (
Table 5.1). This revealed that the changes brought by Big Data are generally managed as any other organizational changes introduced to the company.

4.1.2 Changes that companies have applied with the introduction to Big Data

In order to examine which changes companies usually apply with the introduction of Big Data, we asked from the respondents to select the main changes from a given list. The changes in this list were created based on the theories previously described in the literature review. The respondent had to indicate the relevance of the changes on a scale of 1 (not relevant) to 5 (very relevant). The participants also had the option to suggest other changes.
These changes were then ranked based on the calculations of the median and the mode, as shown in Table 5.2 in Appendix B. The mean was also calculated but not used for the ranking process, as it is not an appropriate measurement to use with a Likert scale (Allen and Seaman, 2007).

The findings indicate that the most relevant changes mainly relate to the technology and the technical aspects involved (the mode and the median is equal to 5 for both). The relatively low standard deviation also shows that the respondents have a consistent perspective on these two aspects (only a few people indicate a score far from the mean).

Technological and technical changes are followed by changes in skills and knowledge, with a median equal to 4 and again, a low variability (standard deviation equals to 1.018).
In the fourth position, the changes in relation to the decision making process are found (with high variability), along with changes in data security policies and regulations (both have mode = 3 and median = 3).
The last and most critical changes regard the corporate culture and the leadership style. Both of them have a high standard deviation (respectively 1.443 and 1.26) and the highest number of missing values ("I don´t know"). In essence, this means that participants are unsure and their opinions vary about whether corporate culture and leadership should be changed after the introduction of Big Data in the company.

The distribution of the collected data is shown in **Error! Reference source not found.**, which illustrates that technical changes are considered relevant or very relevant by 88% of respondents, changes in technologies by 86%, and skills and knowledge changes by 80%. A 46% of the participants agree that changes in the decision-making process are relevant or very relevant, while 25% think that they are moderately relevant.
A 34%, 23% and 27% of the participants considers the changes in data policies and regulations, the company culture, and leadership style, respectively, moderately relevant.

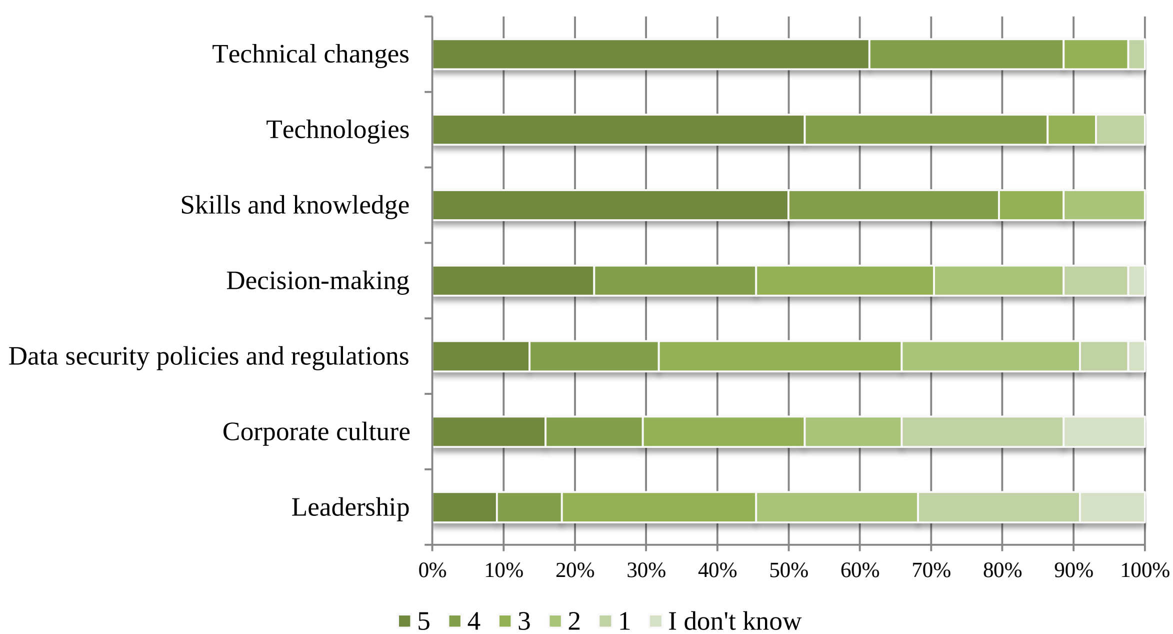

Figure 4.2: Frequency distribution of the changes

Lastly, participants have also indicated other changes referring to strategies necessary for companies that provide Big Data services, such as "We need to change our Sales Engagement and

Sales Speech”. However, such changes are considered as irrelevant and they are not included in the findings, since this study focuses on the internal use of Big Data.

4.1.3 Examining the correlation between the changes

In order to understand if there is a relationship between the different changes, the Spearman's rho was calculated (see Table 5.3 and Table 5.4 in Appendix B) and a statistically significant positive correlation was discovered between the changes in:

- leadership style, decision-making process, and company culture
- skills and knowledge, technologies and technical changes.

On the other hand, changes in data security policies and regulations do not show any statistically significant correlation with any other changes.

Consequently, in order to avoid redundant measures and find possible group indicators of the changes, we employed a factor analysis in relation to the different indicators of change. We excluded the changes in data security policies and regulations from the analysis, due to the lack of significant correlation with other indicators. The principal components analysis confirmed the existence of two important underlying factors (where eigenvalues were greater than 1 and explains 75% of the variation in the questionnaire variables). Figure 4.3 indicates the values of the first two components, which were used for their interpretation.
In conclusion, the first factor (vertical axis) measures the tendency to consider changes in, what we decided to call *cultural aspects*, as important. The highest loading variables in the first component are as follows:

- change in the decision-making process
- leadership style change
- change of the company culture.

On the contrary, the second factor (horizontal axis) measures the tendency to consider *corporate resources* as important changes that are required by the introduction of Big Data. The variables that were loaded onto this component are:

- technical changes
- skills and knowledge change
- change in technologies

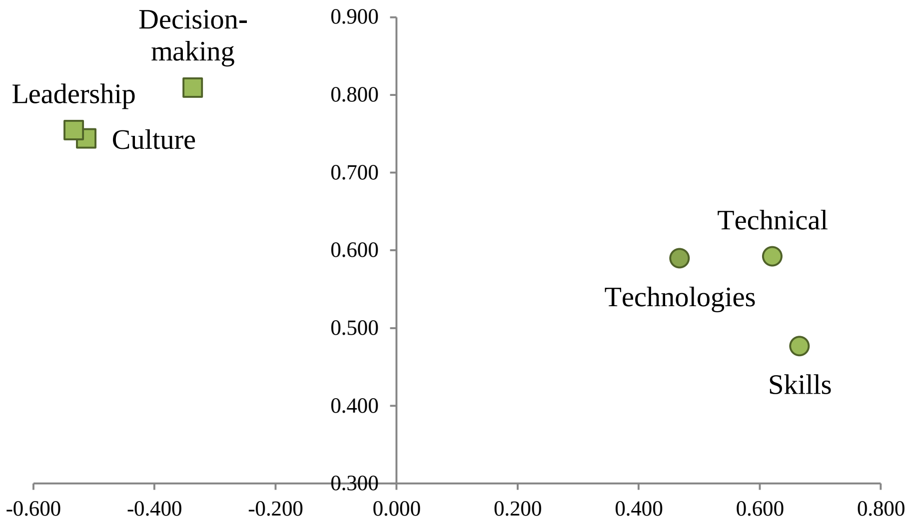

Figure 4.3: Factor analysis of changes: values of the components

4.1.3.1 Corporate resources

The main changes that respondents consider as most important–for using Big Data refer to the technical and technological aspects, and the relevant skills and knowledge. In addition to the survey results, all interviewees confirmed that technical and technological changes are important and necessary to receive the best results of Big Data. They were described as the starting point, the fundamental change challenge that had to be overcome before focusing on other aspects. However, most managers recognize the need of doing more than that; during an interview, the CTO of a consultancy company explained that “technical skills are used to analyze the data”, although a firm would also need a person that based on the provided data will make the right decisions.

As previously illustrated, 80% of the participants stated that skills and knowledge are seen as “relevant” and “very relevant” aspects to change. The literature on Big Data abounds with arguments about which skills or knowledge are necessary to overcome related challenges, however, our aim was to understand, which of them are the most relevant, how they differ from the traditional ones used in Business Intelligence and thus, which should be recommended for companies to acquire.

Therefore, the following question was added in the questionnaire: “How important are the following skills and knowledge for working with Big Data?”, followed by a suggested list of skills (based on literature). The responses were provided in a 5-point Likert scale format, while the participants had the possibility to answer “I don’t know” and/or indicate additional skills.

The measures of the central tendency of the results are shown in Table 5.5 in Appendix B. Complementary skills appear to be the most popular, with a mode and median being equal to 5 (very relevant, 48% of respondents). Additionally, statistical skills were "very relevant" as it was the most frequent response (45%) but with a median equal to 4. Communication and teamwork followed with a median equal to 4 and mode equal to 5, while problem-solving and general business knowledge had a median and mode equal 4. IT knowledge is the second to last in the list, however it got a high percentage, as 57% participants consider it relevant and very relevant. On the other hand, knowledge in ethics is considered as moderately and slightly relevant by a 54% of participants, while 9% of them expressed no opinion about it (median = 3 and mode = 2).

Complementary skills were in the first position and thus, they was chosen to be further examined in the qualitative analysis.

After the interviews were conducted, it became clear that even though highly complex statistical methods are fundamental tools for exploiting Big Data, they are still not adequate. All the interviewees agree that professionals who work with Big Data should have business knowledge. In particular, a top manager of a consultancy company argued that there is an overconfidence both in statistics and the technology side in general, and that for every statistics expert, companies that wishes to exploit Big Data in the best way need at least one "super skilled" senior business person. This necessity derives from the fact that even though Big Data produces an excessive amount of information, one still needs to know which kind of information that should extract. If statistical tests identify thousands of correlations, only a business expert is able to recognize which relationships offer benefits or impacts the business.

This position is strengthened by a positive, statistically significant linear correlation (the Linear-by-Linear Association in Chi-squares tests had p-value < 0.05) each variable of skills and knowledge in the questionnaire, besides IT and statistics, and the variable which measures how often the respondent worked directly with Big Data. In other words, the more often the respondent worked directly with Big Data, the more they consider business and soft skills (communication, teamwork and problem-solving) as relevant.

4.1.3.2 Cultural aspects

As previously mentioned, changes in the decision-making process, leadership style and company culture resulted in a positive correlation (while a statistically significant correlation was found with the Spearman's rho test). This indicates that the level of relevance of these changes is generally allied to the rest of the changes. A corresponding relationship was also observed during the interviews, when interviewees were asked to elaborate on which changes they also considered as necessary, besides changes in company resources. Decision making, leadership style and company culture were jointly referred to by both CEOs and managers, without inferring any distinctions and suggesting that the three are interconnected.

Moreover, from all the changes that were analyzed these cultural aspects have the largest standard deviation, indicating how controversial they are. In order to clarify this point, we cross-tabulated these three indicators with all the other variables included in the questionnaire. The Spearman's rho test revealed that the perceived relevance of each "cultural" change is statistically correlated (p-value < 0.05) with the respondent's relationship to Big Data; the people who worked directly with Big Data consider the changes in the cultural aspects more relevant than others.

The interviewees revealed that Big Data is best exploited when "the philosophy and the way of thinking" changed towards a Big Data-oriented approach. One of the recommendations was that the working environment should become more open and collaborative as "the value (of Big Data) is higher if it is shared", and that colleagues should be "far more willing to collaborate and create solutions together". Some managers explained that, in their company, decision-makers and analysts are now working closely together, while a CEO argued: "our mindset is that collaboration is the way to go". Other managers added that "with Big Data you cannot work in silos" and also that "if your team is working collaboratively then your solutions will be successful; Big Data has a lot of potential but you need to have the right people with the right experience and motivation". This explains why soft skills are important for working with Big Data, as they facilitate the culture of collaboration among employees and decision-makers.

At the same time, the decision making process should move from an approach based on "gut feeling", intuition and personal experience, to a "fact-based philosophy" or "evidence based decisions", as interviewees explained. Decision makers, together with other stakeholders, should change their mindset, and trust and rely more on data. As a manager confirmed, it is necessary "to have faith in Big Data solutions" and not perceive it as just a "hype", since "it does provide real value". Companies should stop being data-drivers and become data-driven, even if this change does not provide the managers with "personal satisfaction" as the decisions made were not their based on their own "initiative". All interviewees agreed that if the current mindset remains unchanged, the full potential of Big Data will remain locked. One contributing factor may be the failure to exploit one of Big Data's main characteristics; that is velocity. For example, being data-driven could cut down a lot of time, and as an interviewee explained it is no longer necessary to arrange a lot of management meetings for making a decision.

Moreover, working effectively with Big Data requires, what a top manager called, taking a "leap of faith". Investment in technologies and data collection must have a different approach than the one in traditional Business Intelligence. "Usually a company starts with a strategy or an idea and then makes a business case, with a top-down approach". On the contrary, with Big Data, a company should "invest first, and find the value later, which is a completely different way of doing things". That is to say that the most appropriate approach would be saving as much data as possible, "even though you do not know, what you will use it later for"; since this huge volume of data can be used in multiple ways in the future, managers should invest in hiring skilled people and allowing them the time to extract value. Such an approach "makes the investment case completely different" than before. A questionnaire respondent, explained in the comments section that the company, in which he/she worked, “moved from a culture where many ideas were discounted immediately, as they were either too expensive or the data set size made their runtimes too long, to [a culture] where new ideas were embraced and implemented”.

Consequently, the aforementioned changes require change in leadership style as well. Indeed, leaders should inspire employees to work collaboratively and encourage effective communication. A product manager suggested that “without close communication these projects will not succeed”, while a CEO of another firm also confirmed that the company is now looking for leaders “who believe in collaboration”

Moreover, an interviewee with several years of experience in Business Intelligence and in Big Data in particular, explained that in order to reach the full potential of Big Data, a company should understand that it must also be exploited outside the marketing sector, where Big Data is currently, most commonly, used. Such an example is the production process, where, as a manager, explained that “the production machines have some sensors that produce Big Data, which can be used to improve the production process, to increase quality, and to reduce waste”.

4.1.4 How changes can help reach the full potential

In order to understand if a particular change is the key to reach the full potential of Big Data, we asked in the questionnaire if the changes they had implemented in their companies were enough to receive the best results (we will call this variable “varFP”). The question was presented in a “Yes/No” format and responding to this question was set as compulsory. In the analysis, we calculated Pearson chi-square, Fisher's exact test (which was considered appropriate in our case as it computes the "exact" (i.e. correct) p-value even for small data sets) and logistic regression (as it predicts binary outcome using one or more independent predictors).
However, no statistically significant relationship between varFP and any other change was identified, which suggests that none of the changes investigated in the questionnaire has a bigger influence than the others, on getting the full potential of Big Data. The same result was observed, after crossing the factors (cultural factors and corporate resources) and the nature of change (continuous/episodic) with varFP. Therefore, we can conclude that getting the full potential of Big Data is the result combining different changes, and none of them should be overlooked.
In addition, when we asked the interviewees if the changes that they recommended were enough to exploit the full potential of Big Data, some of them admitted that they were not. A CEO acknowledged that the management of changes related to Big Data is still a very immature field, while a consultant stated that companies are “still in a journey and there is a lot to discover”. Moreover, a top manager replied that no single answer exists because “[the result] depends on so many variables [such as] the nature of the change, the data, the nature of the management structure and the competitive dynamic of the industry”.

4.2 Resistance that companies encounter

The second research question that our survey aimed to investigate was focused on the resistance a company can encounter, when changes required by Big Data are implemented. In order to examine this question, we analyzed the causes and the nature of the resistance. From this point on, we refer to resistance caused by employees or decision-makers as *internal resistance,* while all the other causes of resistance are considered as *external resistance*. *General internal resistance* refers to resistance from both employees and decision-makers.

4.2.1 Sources of resistance

To the question "What kind of internal resistance did the company face with the introduction of Big Data?" the results were rather inconclusive and did not provide a clear picture. The reason for this is because 50% of the participants answered that there was no internal resistance. The other 50% of the answers were divided, where a 27% responded that there was a general internal resistance to change, 27% responded that resistance came from decision-makers, 32% resistance from other employees and 14% responded other sources of resistance (Figure 4.4).

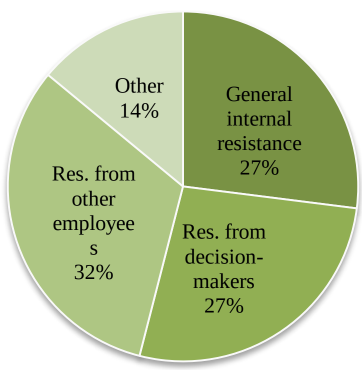

Figure 4.4: Sources of resistance (in percentage)

The participants who selected "other" as a response had the chance to write down their own answer. However, some of these answers seemed to fit under the suggested categories, so we distributed them accordingly and refined our data. For instance, the source of resistance "Trouble convincing the Board" was included in "Resistance from decision-makers".

4.2.2 Causes of resistance

In order to understand how resistance worked inside the companies we asked our participants for the reasons why they opposed to the changes. In **Error! Reference source not found.** the distribution of the answers is shown, while Table 5.2 in Appendix B illustrates the measures of central tendency.

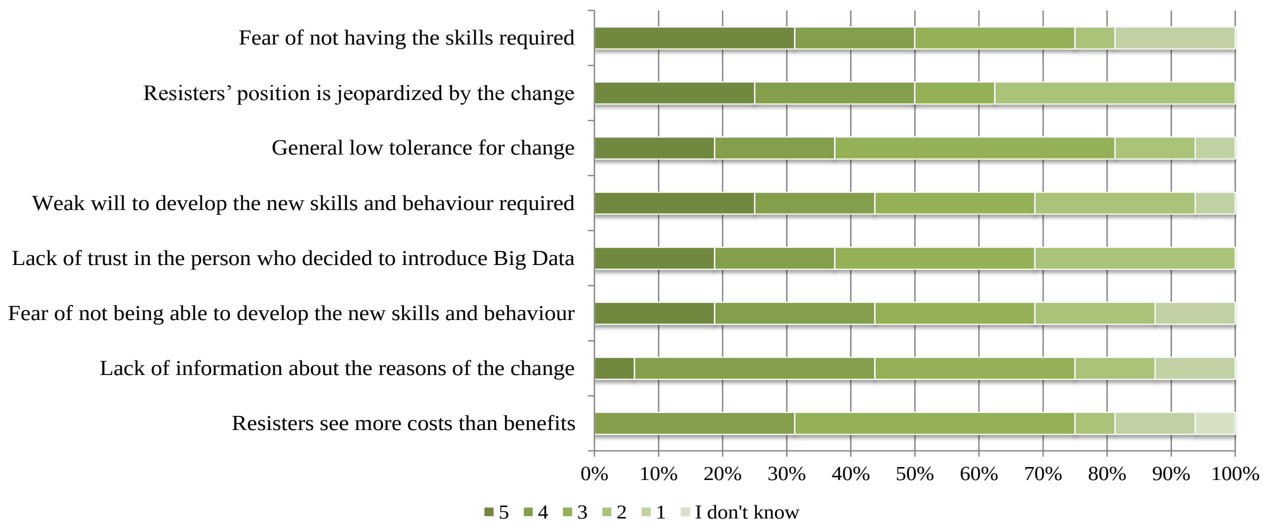

Figure 4.5: Frequency distribution of the causes of the resistance

4.2.2.1 A general internal resistance

When we asked an interviewee how he perceived resistance in his company, he stated that the problem lay in the mentality of the employees and in a certain business philosophy that was not aligned with the philosophy of Big Data. Particularly, he explained that their working force consisted of people experienced in the financial market, which “is historically built on protecting and operating in silos; the philosophy of banks is to protect the information, to protect the algorithms, to protect your thinking and to not share.” Thus, it is a great challenge to convince them to change a mentality that focuses on collaboration. Additionally, other participants mentioned that departmental politics restricted the sharing of data between the departments.
Furthermore, a participant indicated that they observed a confusion regarding Big Data and that people tended to ignore its presence. Considering the recent appearance of Big Data and its technological nature, it is possible that these people did not have adequate knowledge about Big Data or its importance for the company, or they might have considered it irrelevant to their work.

4.2.2.2 Resistance from decision-makers

The survey results revealed that decision-makers tend to resist due to lack of information about the reasons why the change was initiated.-Furthermore, they also show a weak will to develop the skills and behavior required for working with Big Data, while another popular reason for resistance is that their position is jeopardized by the change.

During the interviews, we discovered a few more interesting facts. First of all, it became apparent that in some cases decision-makers held a negative attitude towards changing their decision-making process to a more fact-based approach. According to an interviewee, the main issue was that these people were reluctant or refused to trust the validity of the data. Additionally, as managers tend to be overconfident about themselves and changing from relying on their own intuition to relying on the data can have a psychological effect on them (Camerer & Lovallo, 1999), as “they do not want to lose their self-esteem”.

Moreover, decision-makers hesitate to invest on Big Data due to the high cost of acquiring the necessary technology and people. A manager that worked for a subsidiary company brought up the issue of a limiting organizational structure; the parent company required back 42% of their revenue and despite their high profitability, investments were limited. “Had we not had that parent, we might have operated in a lower margin [and] invested more in our business”.

Lastly, an interviewee also confirmed that people “do not see any immediate results from Big Data” so they do not want to take “the leap of faith”, as already discussed in the “cultural aspects” section. Thus, it is challenging to convince the decision-makers of its value or potential, who most of the time prefer using their available budget for more traditional, less risky investments. Additionally, the results from Big Data are not easily expressed in numbers as decision-makers prefer, there is a lot of skepticism from a decision-maker's’ point of view.

4.2.2.3 Resistance from other employees

As previously mentioned, our quantitative analysis revealed that most of the resistance comes from employees who are not participating in the decision-making process. The questionnaire results indicate that the resistance initiated by these employees is caused mainly by the resisters’ fear of lacking the necessary skills to work with Big Data and by their position being jeopardized by the change. These two causes are closely related to each other as they both indicate that the employees’ resistance is highly connected with any fears of not having the ability to keep their position in the company after the implementation of the changes. This fear does not seem to be irrational, since, as an interviewee explained, some companies prefer to hire cheaper, newly graduated workers, rather than training the current ones.

Additionally, many employees lack will to develop the new skills and behavior required. A CEO of a consultancy company mentioned that “some people did not feel comfortable [with the changes] and they continued to do things the old way". They had an individualistic working style and resisted closer collaboration, so in the end the company had to let them go.

4.2.2.4 External resistance

Although analyzing external resistance is not part of our objectives, we extracted some additional information during the interview process, which we thought we should share and maybe raise a point for future research by others in the academic community. As an interviewee explained to us, one of the greatest challenges they face in the company is the resistance of the market, which is highly regulated. Despite big investments on finding solutions with this issue, he admitted that "it has become very difficult to handle the data privacy laws; Largely in Europe and also in the former industries, the regulations are really strong. Moreover, "customers are afraid to give away the data and [the problem] is not just about the trust; it is more about the trust and the privacy in the data". On the whole, "there are a lot of forces in the outside world that try to prevent the potential of big data initiatives to be harvested".

4.2.3 Resistance to change: an in-depth analysis

In the previous sub-chapter we examined how the various stakeholders can become a roadblock during the organizational change process and what drives their resistance. As a next step, we examine how the different variables of change can affect the degree of resistance.

Firstly, we analyzed the relationship between the nature of change (episodic or continuous) and the dummy variable that indicates the presence of resistance. We discovered that there is a statistically significant relationship between those two (Table 5.6 in Appendix B). As illustrated in Figure 4.6, 63% of the respondents that perceived changes as episodic have stated that they encountered resistance, while 72.7% of the participants who viewed change as continuous, said that there was no resistance. Thus, the results indicate that resistance depends on how the change is viewed and on the way it is being implemented.

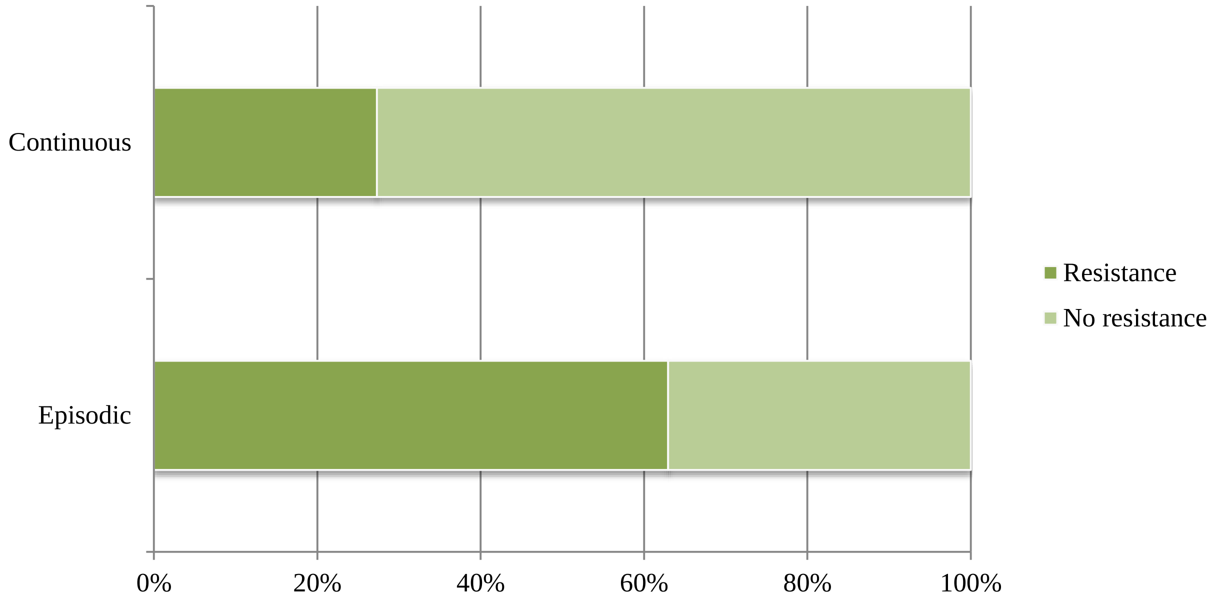

Figure 4.6: Frequency distribution of the nature of change and resistance

Indeed, it became clear during an interview with a product manager that when managers try to implement changes, they realize that the way they will apply those changes can affect the outcome. As the manager explained "of course I would like to move in a fast way", however, it is important to give enough time for this process to evolve and minimize resistance as much as possible. He also added that changing towards an environment that will allow the company to reach the full potential of Big Data requires time that will allow the culture to evolve and progressively adapt.

Furthermore, another interviewee that works as project manager in a consultancy company also confirmed that they managed to implement changes without encountering resistance. As he explained they implemented changes in a slow and gradual manner. On the contrary, another manager told us that he prefers following a "let's do it at once" approach, which he believes that "it is a little more shocking but the shock is small, short and done at once". He also explained to us that he recommends that there should be "phases of change that do not overlap with each other". Lastly, he added that "whether people will accept the radical changes or not, also depends on every case, so you have to be very careful.

In general, the interviewees confirmed that, regarding continuous change, less resistance was encountered by all parties.

4.2.4 How changes affect resistance

Finally, we cross-tabulated the data that were gathered from the different changes that the companies implemented with the source of resistance. The most important findings are presented below.
According to the responses in the questionnaire, 40% of the participants that encountered no resistance stated that a change in leadership style is irrelevant, while another 40% stated that it is slightly or moderately relevant. Furthermore, resistance from employees, who do not participate in the decision making process, is positively correlated with changes in leadership style (p-value <0.005), therefore, we can assume that the more relevant is the change in leadership style, the higher is the probability of resistance from employees (not involved in decision-making).

Furthermore, the correlation indicated that the more relevant is the change in skills and knowledge, the lower is the probability of encountering resistance (p-value > 0.05). This discovery was particularly interesting, since it presented a great contradiction with our previous findings, where it was discovered that one of the main causes that employees usually resist is due to their position being jeopardized by the change. In an attempt to explain this contradiction, we would like to elaborate on a critical observation that derived from our experience during an interview. A CEO claimed that in his company everybody worked efficiently as a team, under close collaboration, and thus there was no resistance. However, at a later point during the interview, he told us that some employees preferred working individually, thus, as Big Data required a more collaborative mentality, these employees did not fit into the company's "open" working environment, so in the end the company had to let them go. In our perspective, this presents an example of resistance, however the manager did not seem to see it that way, since he thought it was an issue that could be simply overcome by hiring new employees with the skills and knowledge that Big Data required. Therefore, a possible explanation is that managers perceive resistance in a way that is different from our perspective. However, this is just an example and no other evidence found was found, that can provide an alternative explanation.

4.3 Solutions to internal resistance

In this chapter examine the strategies or solutions companies implement in order to deal with internal resistance. These strategies into two different categories, where the first one refers to solutions to *prevent* the appearance of resistance, while the second one regards the solutions to *overcome* the resistance after it has already appeared.
Regarding the quantitative analysis, we gathered responses based on whether the participants had encountered resistance or not. With the use of contingency questions, the ones who did not face

resistance were asked about preventing resistance, while the others about overcoming resistance. The two different categories have been analyzed separately and the results are illustrated in Figure 4.7.

Figure 4.7: Frequency distribution of the strategies to prevent and overcome resistance

4.3.1 Strategies to prevent the appearance of resistance

According to the results of the survey Figure 4.7, the most popular strategies to prevent internal resistance include education and communication programs targeted at all employees. Education and communication programs for IT employees, as well as facilitation and support (such as trainings or emotional support) for all employees were also important, while only a few participants chose to involve resisters to the change process. Offering incentives such as higher wage (Kotter and Schlesinger's "negotiation and agreement" strategy) or using explicit and implicit coercion were not taken into consideration by most respondents. Furthermore, only a small number of participants answered that they did not implement any strategies.
One significant finding was that companies that did not follow any strategies to prevent resistance failed to reach the full potential of Big Data (gamma = -1, p-value = 0.049 Table 5.7 in Appendix B). Indeed, as an interviewee explained, people will always resist to change, since "it is in the human nature", thus there will always be the need of applying different strategies to prevent resistance. Subsequently, if the companies do not deal with the resistance in advance, the change process is more likely to be interrupted.

During the interview, we tried to understand the circumstances under which the various strategies would be chosen as the best solution and how participants practically implemented those strategies. According to an interviewee that worked as a middle-line manager in a Business Intelligence consultancy company, "the topic of Big Data was firstly introduced to the company by a technological partner" who gave them advice on how to proceed with Big Data. After "a number of events and meetings" the company earned valuable knowledge which allowed them to prepare themselves for the upcoming change. The manager also added that the partner company "gradually explained the potentiality of Big Data and explained [to the managers] the tools that currently exist in the market". This step was very important to the change management process, since it helped them understand the necessity and importance of Big Data, which in turn also gave them the incentives to want to implement the required changes.

The effectiveness of applying strategies for communication and education programs directed to decision-makers, as well as facilitation and support (trainings, emotional support) for the other employees, is also supported by Kotter and Schlesinger's theory (see literature review).

4.3.2 Strategies to overcome resistance

The first question in this section of the survey referred to the kind of strategies the company had implemented to overcome resistance. The results revealed that the most popular strategies to overcome internal resistance include the implementation of education and communication programs for all employees (including decision-makers and IT employees), as well as strategies that aim on the participation and involvement of the resisters. Education and communication programs specifically for IT employees are also ranked high, followed by education and communication programs for decision makers combined with facilitation and support (trainings or emotional support) for all the employees. While offering incentives is not a common strategy to overcome resistance, it is used significantly more often in this case than as a strategy to prevent the appearance of resistance Figure 4.7.

An in-depth analysis of the practical perspective of the topic was pursued throughout the duration of the interviews by aiming to retrieve the solutions that the interviewees suggested. According to a product manager that works for an insurance company, "close communication with all the different stakeholders" is the key to managing the change. The strategy is "to communicate the value more effectively to the managers", who many times fail to see the value and benefits that Big Data brings. The managers think that "they spent too much [money]", since due to the recent nature of Big Data, many other companies have failed to receive the best out of it, so managers who read these reports hesitate to proceed with it. As a solution, he frequently arranges meetings with the stakeholders so he can explain to them of the opportunities. He added, "50% of the projects are failing because people do not do it in the right way, so I have to constantly make sure we show the potential and convince why our project would be successful".

In addition, when implementing Big Data projects, "the best way is to break this project into small parts and always make sure that the customer is on board" during the whole process, while

maintaining close communication. Another manager that works with Business Analytics, also agreed to that perspective: “What helps drive change, even against resistance, is making strong cases that the change is valuable and just working through the process of bringing people along.” It will require time and a traditional change management process, however, “the insights or the kinds of things you can do differently with Big Data are potentially radical, as radical as dropping a PC on somebody’s desk when they never had one before.”
Regarding the corporate culture, the same admitted that it has slowly been changing; “Our company is a hundred years old company, so the rate of innovation is not much here. It is going to take some time and although we are getting a lot of scrutiny, we are able to manage the roadblocks again by good communication”.

Moreover, another interviewee that has been working as a consultant for years, focused on the potentiality of Big Data. As he stated, “we show people what is new, what is possible when you start bringing these datasets into your environment (...) and the benefits you can get in the traders environment.” Regarding the companies that they work with, he explained that they have to show them the possibilities and different successful cases; “this way you can easily build a brand new value, and it is this type of value that automatically can become a business case.” A Business Analytics Services Director, also emphasized the role of the management team, where he emphasized the importance of having a management team that understand the importance of investing on fact-based decisions”. He supported that decision-makers should “change their mindset to a more data-driven decision making process”, since according to his experience it “has helped making decisions faster”. Therefore, it is important to help them understand that a complete change in the business data is required to receive the benefits of Big Data.

Furthermore, another recommendation is that “managers should trust the data”. In the current business, decision-makers are mainly investing in more traditional approaches and strategies that have been “proved to work for years”. One reason for lack of trust in the data is related to the personality of the managers and decision-makers: “The people that would benefit the most on fact-based decisions do not have that profile; they are more action-based persons”. As the interviewee explained, “Another reason is that, I think that we have not done a good job in the traditional Business Intelligence Data warehouse base, historically. I started in 2003 and since then they still take decisions based on gut feeling”. However, as a response to these problems, the key with Big Data is to think outside of the box and follow a completely different approach. “The mindset will change as the trust will be established, and the trust will be established if you actually invest first. So the focus should be on convincing people and explain to them how it works. This is not an easy task, however, the good thing is that technology now is cheaper”

Apart from the kind of strategies that should be implemented, we asked one of the managers on the way the changes should be implemented. As he explained, “it always depends on the culture that the organization has”. Naturally, most of the organizations are “highly resistant to change”, so he recommended to not necessary implement the changes slowly, but instead set relatively modest goals that can be and achieved quickly. You first have to prove yourself and then you can go for bigger goals". Additionally, change "could undermine certain, long-held assumptions, which people can get very tied to". Usually, they tend to "make long-standing investments and they might have spoken publicly, or to the shareholders, in favor of these assumptions; You have to give time to the organization, in order to start signaling that these assumptions might be wrong. You have to step your way in, to get a buy-in from people that are inside the organization, and then possibly also from external stakeholders".

Moreover, the successful implementation of those strategies highly depends on the ability of the manager to overcome the obstacles and his/her leadership style. As an example, the same manager told us: "Imagine if you were to come up with a fundamentally business-changing solution. That is going to be very hard to accept, unless you have a truly visionary CEO that is willing to turn the company on a dime".

4.3.2.1 Measuring the success of the strategies

Onwards, we asked the questionnaire respondents whether they thought that the implemented strategies were successful in overcoming resistance. The results at this point were rather disappointing, since they did not provide a conclusive answer. More specifically, 29.4% of the respondents answered "Yes", 11.8% answered "No", while 52.9% answered that they did not know. Almost 6% of the participants chose "other", while one of them wrote that the changes worked partially. However, the biggest issue lies in the fact that more than half of the participants were unable to identify the effectiveness of the results. In an effort to find more conclusive answers, we tried to study the effectiveness of each strategy, although we concluded that there is no significant correlation between the applied strategies and their outcomes.
In addition, overcoming strategies are neither correlated with the causes of resistance, which indicates that the theory of Kotter and Schlesinger (2008) that associates a specific strategy to a specific cause of resistance (see literature review), is not applied.

An additional aspect that we analyzed is preventive formal communication. In the questionnaire we asked if the introduction of Big Data was communicated to all the employees, and if yes, how (through E-mails from organization's executive management, materials posted in break rooms, on bulletin boards or elsewhere on organization, information posted on company Web site or intranet, etc.). On 44 participants, 43% answered "yes", 34% "no", and the remaining 23% answered that he/she does not know it (probably because he/she was still not working in that company before the introduction of Big Data).
Finally, we cross-tabulated this variable with a dummy variable (obtained by the responses to the question "What kind of internal resistance did the company face with the introduction of Big Data?"), which indicates the absence (with value 0) or presence (with value 1) of resistance to

change. We did not find any statistically significant correlation between these two variables (p-value > 0.05). Regardless, the frequencies indicated that among the companies that did not communicate the introduction of Big Data, 66.7% reported that they encountered resistance, while among the companies that had initial communication, only 37% encountered resistance).

4.4 Discussion

In the light of the final results from the analysis, the conclusion can be derived that the majority of companies do not follow any specific models or best practices to manage the changes brought by Big Data. Each company manages the changes in different ways, while sometimes even overlooking important aspects, such as the company culture. However, the common attribute that these companies share is that they generally manage the changes that Big Data requires in a similar way that any other organizational change would be managed. Although almost 63% of the questionnaire participants see the change from an episodic perspective, the traditional episodic approaches to change do not seem to be enough. Indeed, episodic changes put too much emphasis on short-run adaptation, however, Big Data keeps on changing over time, at a very fast pace. There is a need to turn to a rather more continuous view of the change, which will help building an organizational structure that allows for long run adaptability; not only the current changes but also any possible changes that Big Data will require in the future.

Listening to managers who work with Big Data and that have years of experience in the field of Business Intelligence has been enlightening. It became clear that besides changes in the companies' resources (technologies, skills and knowledge), the cultural aspects should not be overlooked. Having powerful machines, buying the latest analytical tools, and hiring super skilled data scientists is essential, although not enough for reaching the full potential of Big Data. On the contrary, cultural changes are also necessary because the existing approaches, inherited from the traditional Business Intelligence, are no longer effective.
Our research therefore confirms McAfee and Brynjolfsson's theory (see literature review) and, on the same time provides some additional interesting findings.

Firstly, companies seeking to exploit Big Data in the most productive approach should integrate a system of values that favors close collaboration and knowledge sharing among colleagues into their corporate culture; with particular emphasis being place on the cooperation between data specialists and decision-makers. The statistical techniques required to successfully analyze Big Data are so advanced that skilled data professionals are considered indispensable. However, they need to be supported by both analysts who possess business knowledge, and open-minded decision-makers, who are able to understand the findings, in order to extract new value for the business. With the absence of data analysis or business knowledge, it is relatively easy to fail to

derive meaningful inferences or get lost in an ocean of correlations, however a team with complementary business knowledge and data analysis skills could potentially avoid this issue.
Consequently, soft skills, such as teamwork, communication and problem-solving skills are required in all the employees who work with Big Data, regardless of their job position or responsibilities in the company. Moreover, complementary skills (that cover the field of IT, statistics and general business knowledge) are indispensable for analysts, while data engineers should possess knowledge of the latest statistical techniques.
This view is also supported by McKinsey, a multinational management consulting firm, which claims that it is important to hire specialists that are "capable of bridging different functions within the organization and effectively communicating between them" (McKinsey in Chandran, 2014). McKinsey calls these specialists "translators" and argues that, in order to be effective, employees need complementary skills coming from different fields such as IT and finance. However, according to a McKinsey survey (Callinan, Edelman & Hieronimus, 2014), only 18 percent of companies believe they have the skills necessary to gather and use insights effectively. In order to leverage the full potential of analytical insights, forming groups of people with complementary skills should be pursued, and the creation of necessary connections between them. "While companies do not often think about talent in terms of value chains, the skill and capability links between people are crucial for unlocking the full value of advanced analytics" (Ariker, Breuer & McGuire, 2014).
Secondly, changing the company culture requires that leaders put effort into effectively communicating this new philosophy to the employees by encouraging close collaboration, knowledge sharing and teamwork. Moreover, companies should try to take advantage of other opportunities by using Big Data not only in marketing or R&D, but also in other sectors, such as production and operations, even if this investment requires, what one interviewee called, the "leap of faith".
Finally, decision-makers should change their mindset, shifting from a decision-making process that is based on their "gut feeling", to a more data-driven approach. If a proper analysis is conducted, Big Data can be very reliable and conclusive and should be used to drive the decisions and to create new value, instead of as a tool used in justifying the intuition and consequent choice of a decision-maker.

Once the company has acknowledged that these changes are fundamental, it should work on preventing any possible internal resistance. Indeed, the analysis shows that the companies that did not follow any strategies to prevent resistance have failed to reach the full potential of Big Data.
As previously mentioned, there is no significant correlation between strategies employed by companies to prevent or overcome resistance and the causes of the resistance. This means that the recommendations of Kotter and Schlesinger (2008) are not entirely applied, because, as we explained in the literature review, the author's idea is that the response to resistance should be chosen in response to its specific causes.

Aversion to change could come from both decision-makers (who, as explained, should change their mindset) and all the other employees, who will have to deal with new technologies, new techniques, the need of new skills and knowledge, and a new corporate culture. The analysis shows that the most popular strategy to prevent internal resistance include education and communication programs targeted at all employees. This confirms Kotter and Schlesinger´s statement (2008), who postulate that "one of the most common ways to overcome resistance to change is to educate people about it beforehand". Instead of forcing all employees to change their normal work process, the firm should first educate its personnel on the topic of Big Data, explaining the motivation behind the decision to introduce this new resource and showing the potential benefits that will be gained from properly exploiting this technology.

Organizing education and communication programs specifically for decision-makers is also a recommended strategy. First of all because, as shown in the previous section, the main cause of resistance from decision makers is lack of information about the reason of the change. This strategy is also recommended by Kotter and Schlesinger targeted to this cause of resistance. Second, education and communication programs can help decision-makers change their mindset, learn to trust the data and be driven by it. Therefore, companies can ask for support from technological partners, such as firms that sell analytical tools to customers.

Moreover, facilitation and support will be addressed to those employees whose resistance is caused by the fear of not having the skills required for working with Big Data (Kotter and Schlesinger (2008). These employees are mainly those who do not participate into the decision-making process. In addition, this strategy should include training programs and in-house education as suggested by Kotter and Schlesinger (2008), which will provide them with the previously mentioned new skills, required to work with Big Data. Finally, for employees who are resisting as a result of their position being jeopardized by the change, negotiations and agreements are necessary (Kotter and Schlesinger, 2008).

Therefore, if a company would try to overcome resistance when introducing Big Data, a strategy that has the most chances would be implementing smaller changes with gradual step, which gives time for people to prepare and helps them adopt.

5 Conclusion

Change management theories are of great importance in order to understand how companies should deal with Big Data. However, no relevant academic literature is currently available on this topic. An exception is the perspective of McAfee and Brynjolfsson (2012) who explain that Big Data is not just a matter of technologies and technical skills, but that it involves managerial and cultural aspects. Nonetheless, the authors do not elaborate any further.

5.1 Research Aims and Objectives

Thereby, the aim of our research was to examine how companies should manage the change in order to reach the full potential of Big Data. The results did not fulfill our expectations because this field is still immature and even practitioners with many years of experience do not have all the answers. As a consequence, we are not able to give a perfectly finished model of strategies that companies should implement. However, we can provide the readers with good advice.

The objectives of this research were to discover (i) what changes companies should make, (ii) what kind of resistance they could encounter and (iii) how they should deal with it, in order to reach the full potential of Big Data. To accomplish this, we have investigated how companies behave towards the transition of using Big Data, and we have analyzed the collected data from a change management perspective. Particularly:

(i) Our findings confirm McAfee and Brynjolfsson's theory, while they also provide other interesting conclusions: in order to exploit Big Data potential at best, corporate culture should be anchored to a system of values that favors close collaboration and knowledge exchange among colleagues, especially between data specialists and decision-makers. Consequently, leaders should encourage collaboration and knowledge sharing, while soft skills such us communication, teamwork and problem-solving should be pursued. At the same time, decision-makers should change their mindset, shifting from a decision-making process based on their "gut feeling" (as in traditional BI) to a data-driven approach.

(ii) As regards the consequent resistance, it can originate from both decision-makers and other employees. For decision-makers, it mainly results from the lack of information about the reason of the change, while among all the other employees who do not participate into the company decision-making process the main cause of resistance is the fear of not having the skills required. Low tolerance for change and parochial self-interest are the two most popular causes of resistance for both the two categories.
An additional interesting finding is that companies where Big Data brings episodic changes have higher probability to encounter resistance than the company where Big Data brings continuous changes.

(iii) In order to get the best results from the change, companies should work to prevent and/or overcome this particular resistance. First, companies should organize education and communication programs for decision-makers, since the main cause of their resistance is lack of information about the reason of the change, as recommended by Kotter and Schlesinger (2008). Additionally, it can help them change their mindset by learning to trust data and to be driven by it. Second, in the light of the causes of resistance identified in the analysis, facilitation and support initiatives for all the employees, and negotiation and agreement strategies are recommended (Kotter and Schlesinger, 2008). However, the survey reveals that companies overlook the latter strategy, favoring education and communication programs for all the employees, and participation and involvement of the resisters.
Finally, when introducing Big Data, a strategy that has the most chances to overcome resistance would be implementing smaller changes with gradual steps, which gives people the time to prepare and adapt to change.

5.2 Practical Implications

These findings can contribute to the development of change management strategies of companies that want to introduce Big Data in their decision-making process. The necessary cultural change is sometimes overlooked, and this research highlights its importance. Furthermore it is a reminder of the importance of preventing and if necessary, overcoming resistance by giving some useful recommendations on how to deal with it.

5.3 Future Research

In order to create a conclusive and comprehensive model of change management to accompany the implementation of Big Data, more research in this area is necessary. Particularly, the analysis of approaches of companies in stabilizing a new state after changes have been implemented while preventing the firm from regressing into the previous state (Lewin's refreezing phase) would be of interest. The personnel given the responsibility of handling the change process would be a great contribution to this field.

Moreover, strategies to prevent and overcome resistance to change require further studies. Further details on conducting education and communication programs in relation to change management, with the inclusion of areas that should be given extra focus and the duration of these programs (for example, if just for the initial phase or longer) would be rather helpful to companies.

In conclusion, applications of change management on the various challenges brought by Big Data has yet to be explored. However, it is apparent that its contribution can be of great significance and it could be the key for unlocking the full potential of Big Data.

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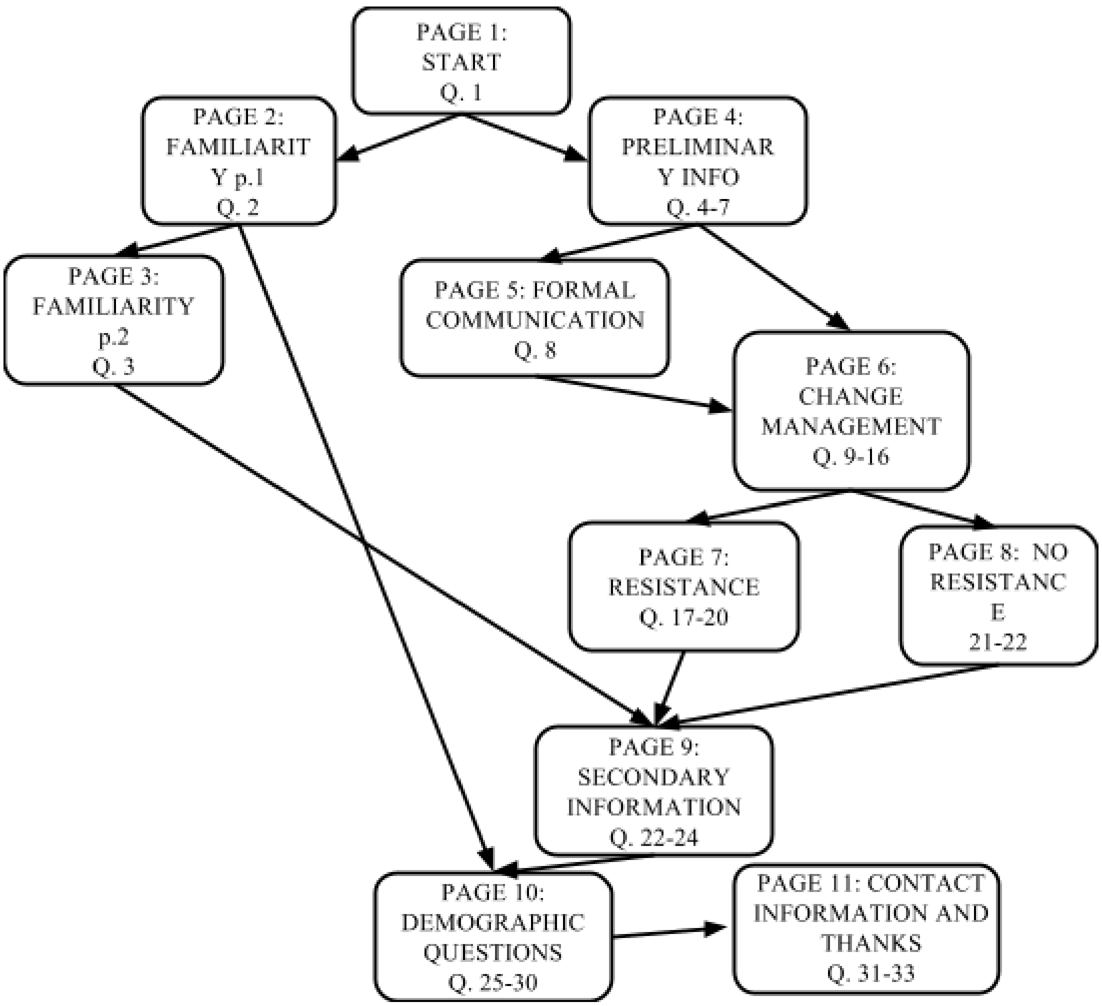
Appendix A

Survey questions

1. Does your organization work with Big Data? *
2. Are you familiar with the concept of Big Data? *
3. How are you familiar with the concept of Big Data? *
4. What is your relationship with Big Data?
5. How long have you been working with Big Data? (directly and indirectly)
6. Which business functions in your company rely most on Big Data?
7. Was the introduction of Big Data communicated to employees? *
8. How was the introduction of Big Data formally communicated to employees?
9. Which of these statements best applies to how change is managed in general in your organization?
10. Which of these statements best applies to how the change brought by Big Data was managed?
11. What are the main changes that the use of Big Data required in your company? *
12. Are there any other changes not mentioned in the previous question?
13. Did you see any benefits after implementing Big Data-oriented changes?
14. Did you see any other benefits not mentioned in the previous question?
15. Do you think these changes are enough in order to reach the full potential of Big Data?
16. What kind of internal resistance did the company face with the introduction of Big Data?
17. What were the causes of this resistance? *
18. Were there any other causes not mentioned in the previous question?
19. What strategies has the company implemented to overcome this resistance? *
20. Did these strategies work? *
21. What strategies did the company implement to prevent resistance? *
22. In your opinion, what are the main characteristics of Big Data?
23. In your opinion, how important are the following skills and knowledge for working with Big Data?
24. Are there any other skills and knowledge not mentioned in the previous question?
25. What is your job title? *
26. What is your age group?
27. How long have you been working at your current company?
28. Where is the office of the company you work for located? *
29. In which of the following industries does your company operate?
30. What is the size of your company? *
31. Would you be interested into participating in a short interview regarding this topic?* The interview will be used as additional support to the findings of this survey and help us provide more accurate results in our research. We are interested in interviewing professionals with insight into this field and gain an inside view of the practical aspects of the connection between Big Data and

Change Management. The interview is expected to have a short duration. However this is negotiable and can be agreed upon depending the availability of time of the interviewee.
32. What is your e-mail address? (optional) Your email address will be kept confidential and it will only be used to send you the results of this survey.
33. Any comments about this survey are welcome:

Survey flowchart



Appendix B

Table 5.1: Measures of relationship between general change management and Big Data change management

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	1.130	.000
	Cramer's V	.565	.000
	Contingency Coefficient	.749	.000
N of Valid Cases		44	

Table 5.2: Measures of central tendency and dispersion of changes

Statistics

		Technical changes	Change in technologies	Change in skills and knowledge	Change in the decision-making process	Change in data security policies and regulations	Change of the company culture	Change in leadership style
N	Valid	44	44	44	43	43	39	40
	Missing	0	0	0	1	1	5	4
Mean		4.45	4.25	4.18	3.33	3.07	2.85	2.55
Median		5.00	5.00	4.50	3.00	3.00	3.00	2.50
Mode		5	5	5	3	3	1a	3
Std. Deviation		0.848	1.081	1.018	1.286	1.142	1.443	1.260
Minimum		1	1	2	1	1	1	1
Maximum		5	5	5	5	5	5	5

a. Multiple modes exist. The smallest value is shown

Table 5.3: Spearman's rho for the correlation between changes

Correlations

			Change in skills and knowledge	Change in technologies	Technical changes
Spearman's rho	Change in skills and knowledge	Correlation Coefficient	1,000	,568**	,515**
		Sig. (2-tailed)		,000	,000
		N	44	44	44
	Change in technologies	Correlation Coefficient	,568**	1,000	,417**
		Sig. (2-tailed)	,000		,005
		N	44	44	44
	Technical changes	Correlation Coefficient	,515**	,417**	1,000
		Sig. (2-tailed)	,000	,005	
		N	44	44	44

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5.4: Spearman's rho for the correlation between changes

Correlations

			Change in leadership style	Change in the decision-making process	Change of the company culture	Change in data security policies and regulations
Spearman's rho	Change in leadership style	Correlation Coefficient	1,000	,739**	,768**	,151
		Sig. (2-tailed)		,000	,000	,354
		N	40	40	39	40
	Change in the decision-making process	Correlation Coefficient	,739**	1,000	,671**	,285
		Sig. (2-tailed)	,000		,000	,064
		N	40	43	39	43
	Change of the company culture	Correlation Coefficient	,768**	,671**	1,000	,134
		Sig. (2-tailed)	,000	,000		,415
		N	39	39	39	39
	Change in data security, policies and regulations	Correlation Coefficient	,151	,285	,134	1,000
		Sig. (2-tailed)	,354	,064	,415	
		N	40	43	39	43

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5.5: Measures of central tendency and dispersion of skills and knowledge

Statistics

		Compl. skills	Statistics	Communication	Teamwork	Problem-solving	General Business knowledge	IT	Ethics
N	Valid	40	43	42	42	43	43	43	40
	Missing	4	1	2	2	1	1	1	4
Median		5.00	4.00	4.00	4.00	4.00	4.00	4.00	3.00
Mode		5	5	5	5	4[a]	4	3[a]	2a
Minimum		1	2	1	1	2	1	1	1
Maximum		5	5	5	5	5	5	5	5

a. Multiple modes exist. The smallest value is shown

Table 5.6: Measures of correlation between the perspectives on the nature of change and resistance

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3,993[a]	1	,046
Likelihood Ratio	4,089	1	,043
Linear-by-Linear Association	3,888	1	,049
N of Valid Cases	38		

Table 5.7: Values of the Gamma test for the relationship between applying preventive strategies and the full potential of Big Data

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Ordinal by Ordinal	Gamma	-1,000	,000	-1,970	,049
N of Valid Cases		24			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.