UiA University of Agder

Master

Organizational culture as a primary driver for utilizing big data analytics in organizations

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Foreword

We are two students attending the master's degree programme, Information systems, at University of Agder. We have previously worked together in most of the projects throughout the programme and decided to also do this thesis together.

Every project we have done throughout the degree where we had an option to choose the topic of big data, it has been chosen. We have always had an interest in this topic and always wanted to improve our knowledge in this area. When we were deciding the topic of this master's thesis, we instantly agreed and proceeded with the topic. We have mostly been interested in the practical use of big data, rather than the academic perspective. But throughout this master's thesis, it sparked an interest in both of us regarding the academic perspective.

We want to thank our supervisor, Professor Ilias Pappas at UiA and Ph. D candidate Frank Danielsen for great help throughout this process.

Abstract

Context: During this last decade we have witnessed a wave of digital disruption, where big data has had a central part. This has gotten many organizations to pay attention and investing in analytic tools for big data. Big data analytics can provide organizations with more knowledge from more data sources that can have a big impact on how organizations act. Many of the organizations that have purchased big data analytics have failed to derive benefits from it and this is demonstrated in the literature. Organizational culture is mentioned as being an important part of achieving success when adopting big data.

Purpose: The purpose of this thesis is to investigate the effect that organizational culture has on big data adoption, more specifically the organizations big data analytic capabilities. To measure this, we looked at the organization's performance.

Methods: We decided to use a quantitative approach to answer the research question. In order to define the different constructs of this research, we conducted a systematic literature review where we based the study on. We conducted a survey that we distributed to organizations within Europe that were using big data. The items of the survey were carefully developed by looking at previous measurements of these constructs and evaluating them with our supervisor, Ilias Pappas. We managed to get 104 respondents where they were all using big data in their work. We then developed a model with three different hypotheses and analysed the response by using partial least square path modelling (PLS-SEM). This was done by using the tool, SmartPLS.

Results: Our analysis validated our three hypotheses. The first one that focused on the positive effect organizational culture have on big data analytic. Second, organizational cultures positive effect on big data analytic capabilities. Final, hypothesis showed that organizational culture had a positive effect on intangible resources.

Conclusion: We can conclude the research by confirming that organizational culture has a huge effect on big data analytic capabilities and organizations need to look at organizational factors as well as the technical when they are investing in big data solutions.

Keywords: Big data, big data analytics, big data analytic capabilities, organizational culture, firm performance

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1.0 Introduction

Eric Schmidt, CEO of Google at the time, stated in Google Cloud Next '17 conference: "I think that big data is so powerful that nation states will fight over how much data matters, right, that he who has the data, that can do the analytics and the algorithms Fei-Fei talked about at the scale we're talking about, will provide huge nation state benefits in terms of global companies and benefits for their citizens and so forth and so on (Youtube, 2017, 2:06:20)." Even though some might argue that big data only has become a buzzword, catchphrase or hype, big data has still a valuable role in organizations. The importance of analytics and big data seems to be a consensus among academia and practitioners. Since the internet became a part of everyone's life, we are constantly connected through mobile devices, social networks and "internet of things", that generate a huge amount of data. This data is referred to as *big data* (Wamba, Akter, Edwards, Chopin & Gnanzou, 2015).

Over the last decade, the business world has been shaken by a remarkable wave of digital disruption that is impacting the way organizations compete (Weill & Woerner, 2015). This is pushing today's societies into a continually expanding digitalized world, where information and knowledge gets available to more and more people. The different digital media platforms, digital services and technologies is changing the way societies are organized, and how their members interact with each other. Organizations are starting to realize that the massive amounts of data that are being generated, can provide them with a competitive edge (Pappas, Mikalef, Giannakos, Krogstie & Lekakos, 2018). Big data, however, are also challenging existing modes of business and well-established companies (Pappas et al., 2018). Solving this so that these technologies can be incorporated into competitive strategies has been a goal of academics and practitioners. The main focus however has been on the technical aspect of big data, and less on the organizational changes (Mikalef Pappas, Krogstie & Giannakos, 2017). This is causing organizations to have problems utilizing big data to improve their organizational performance (McAfee & Brynjolfsson, 2012), as it requires them to overcome a number of challenges, one of them being the organizational culture (Manyika, Chui, Bughin, Dobbs, Roxburgh & Byers, 2011).

Organizational culture in relation to big data has been studied in the literature. Many of the papers highlight that organizational culture has a critical role in the success of big data initiatives and is often the main reason why big data initiatives fails, rather than technological factors (Shamim, Zeng, Shariq & Khan, 2018; LaValle et al., 2011).

With organizational culture having such a strong impact on various aspects of an organization, such as strategy, structure, and processes, many of the obstacles in relation to big data, are more than likely to be related to organizational culture and not to data or technology (Alharthi et al., 2017). The literature exposed a need for knowledge surrounding organizational culture in the field of big data.

The goal of the study is to understand the impact that organizational culture has on big data analytic capabilities and the organizations performance. We are proposing the following research question for this thesis:

“To what extent does organizational culture affect an organization's ability to adopt and use big data?”

To answer the question, we tried to look at the topic through a resource based view, where we looked at the organizations big data analytic capabilities and the resources needed to develop these capabilities. We conducted a study consisting of three phases. First, we conducted a systematic literature review to get an insight into the existing knowledge within this field. Next, we developed a conceptual model and a survey. We ended phase 2 with the distribution of the survey. Phase 3 was used to collect the data and perform data analysis and finish up the project. simultaneously with all these three phases, we developed the report.

In the second and third phase, we managed to collect 104 respondents that were using big data actively in their organization which we analysed.

1.1 Key concepts

In academia, “big data” and “big data analytics” are often used interchangeable. We have followed these definitions when addressing these terms.

Big data: The terms big data is used to describe the massive volume of digital data produced by human activity that is very difficult to manage using conventional data analysis tools (Alharti, Krotov & Bowman, 2017). Big data cannot be defined just by volume of data, but also by high velocity, diverse variety, exhaustive in scope and relational in nature (Kitchin, 2014).

Big data analytics: Big data analytics are used in this research where it is a term to describe the denotation of data management technologies and computer-based analytical tools for discovering valuable information for decision making (Alharti et al., 2017).

Organizational culture: Is a set of shared assumptions that guide what happens in organizations by defining appropriate behavior for various situations (Ravasi & Schultz, 2006). Organizational culture affects the way people and groups interact with each other, with clients, and with stakeholders. Also, organizational culture may influence how much employees identify with their organization (Schrodt, 2002).

1.2 Motivation

Since the beginning of our academic degree, both of us have had an emerging interest of data analytics and big data. We have always looked at big data as a catchphrase, but also as a useful technology for organizations. We wanted to look deeper into the organizational aspect of big data. We decided to write about big data because the technology is relatively new, and it sparked an interest in us.

1.3 Content and structure

We have decided to structure the report as follows: chapter two is the theoretical foundation. Chapter three will describe our conceptual model and the hypotheses. The fourth chapter is the methodology that was used throughout this thesis, and the fifth chapter describes the findings after we applied the described methods. Chapter six and seven is the discussion and conclusion. Lastly, we present the references and the appendix.

2.0 Theoretical foundation

The theoretical foundation of this thesis is based on an extended systematic literature review. In addition to gathering all our research from the field of big data, we searched outside to get a clear theoretical foundation for organizational culture. There was not enough data on organizational culture in the field of big data to conceptualize and measure the construct. Most of the dimensions used to build the organizational culture was gathered from Hogan & Coote (2014). They developed their dimensions based on Schein's model of organizational culture, which is one of the leading figures in the field of organizational culture.
During this phase we continually refined our research question and laid the basis for our research model.

2.1 Organizational culture

Organizational culture is an old and well researched area. It is a complex notion that is hard to grasp and has several different definitions described by management scholars, yet there is no consensus on a single definition (Gupta & George, 2016). Organizational culture is often divided into two different ways of describing its meaning. The first suggests that organizational culture is the glue that keeps an organization together, while the second way of describing organizational culture is that it encompasses most of the areas of an organization (Iivari & Huisman, 2007).
When analysing the culture of an organization it is desirable to distinguish three fundamental levels at which culture manifests itself, these are artifacts, values and assumptions (Nguyen, 2018). Schein is the one that developed the three fundamental levels of organizational culture used by Nguyen (2018) and is also the inspiration behind the development of Hogan & Coote`s (2014) eight dimensions. Each of these different dimensions is used to measure the organizational culture and is connected to one of the three levels of organizational culture. These eight dimensions are similar to the seven dimensions used by O`Reilly, Chatman & Caldwell (1991) and Chatman & Jehn (1994) to identify organizational culture. The dimensions are presented in table 1 below.

Organizational Culture by (O'Reilly, Chatman & Caldwell, 1991 & Chatman & Jehn, 1994)	Organizational Culture by (Hoogan & Coote, 2014)
Innovation	Openness/Flexibility
Stability	Responsibility
Respect for people	Appreciation of Employees
Outcome orientation	Success
Detail orientation	Competence & Professionalism

Aggressiveness	Risk-taking
Team orientation	Inter-Functional Cooperation
	Internal Communication

Table 1: Conceptual model

The different dimensions provided in the table shows that there is an overlap between them. By looking through the lens of these dimensions provided by Hogan & Coote (2014), we will get a clear picture of an organization's organizational culture. Organizational culture`s three levels and the dimensions attached to each will be defined in the section below.

2.1.1 Assumptions

Assumptions are the taken-for-granted beliefs about human nature and the organizational environment that reside deep below the surface (Schein, 1990). Assumptions are divided into three dimensions; openness/flexibility, internal communication and responsibility.

Openness/flexibility
Openness & Flexibility refers to the degree that an organization values openness and responsiveness to new ideas (Hogan & Coote, 2014). This may have an impact on creativity, empowerment and change in organizations. It also drives the organization towards new ideas and tolerance, while facilitating new ideas and support the production of creative solutions (Hogan & Coote, 2014).

Internal communication
Internal communication refers to the organization's ability to value and facilitate open communication and information flow within an organization (Hogan & Coote, 2014). This may assist organizations in improving the quality of decision making, while providing access to more diverse knowledge.

Responsibility
Responsibility looks at the employees proactiveness and how likely they are to take initiative and responsibility of their own work (Hogan & Coote, 2014).
When given responsibility of achieving different goals in a project, it will inspire the employees to develop a sense of ownership and control over their own work and ideas. It makes them more likely to overcome potential problems with persistence and determination, and yield more creative outcomes (Hogan & Coote, 2014).

2.1.2 Values

Values are the shared beliefs and rules that govern the attitudes and behaviours of employees, making some modes of conduct more socially and personally acceptable than others (Rokeach, 1973). Deeply held assumptions often start out as values, but as they stand the test of time, they gradually come to be taken for granted and then take on the character of assumptions (Schein, 1990). Values are divided into two dimensions; Risk-taking and competence and professionalism.

Risk-taking
Risk-taking refers to the degree to which and organization values challenging the status quo by experimenting with new ideas and taking risks (Hogan & Coote, 2014). Valuing risk taking or encouraging calculated risks to enhance the workplace is related to psychological safety where the employees have the freedom to experiment with their new ideas without the fear of losing currency in form of status or career. By valuing and supporting risk-taking, it may strengthen the superordinate identity and by combining it with supervisory support, the outcome may influence product innovativeness (Hogan & Coote, 2014).

Competence & professionalism
Hogan & Coote, (2014) defines competence and professionalism as to how much an organization values knowledge and skills and maintain and uphold the ideals and beliefs that is associated with the respective profession. Professional knowledge, expertise and technical skills is often used as the raw material for innovation (Hogan & Coote, 2014). When increasing the professional knowledge, expertise and technical skills in the organization, the ability to analyse problems and develop better solutions will increase.

2.1.3 Artifacts

Artifacts are the more visible language, behaviors, and material symbols that exist in an organization (Schein, 1990). Artifacts are divided into three dimensions; Success, inter-functional cooperation and appreciation of employees.

Success
Success is the extent to which an organization values success and continually strives for the highest standards of performance, while welcoming challenging goals. This also requires encouragement of the employees in the organization (Hogan & Coote, 2014). The success dimension has the potential to raise performance expectations of the employees and make the employees mentally invested in the organizational goals. It can lead to a boost of intrinsic motivation and competence amongst the employees and increase their motivation to find unique solutions to organizational problems (Hogan & Coote, 2014).

Inter-functional cooperation
Inter-functional cooperation is the organizations coordination and teamwork (Hogan & Coote, 2014). When working on projects, members of the organization can consider their tasks to be reliant on expertise, information and resources of other specialist in order to achieve the desired result. Coordination, communication and teamwork will result in high levels of integration and sharing amongst the teams. This will have an effect on the success of the organization (Hogan & Coote, 2014).

Appreciation of employees
Appreciation of employees is how an organization values, rewards and recognizes the accomplishments of the employees (Hogan & Coote, 2014). When an organization is

trying to reach their output expectations, rewarding and giving positive feedback to the employees are proving to be more successful. This is also true for the rewarding of performance and risk-taking (Hogan & Coote, 2014).

2.2 Big data analytic capabilities

In order to obtain the full benefits from big data, managers need to align existing organizational culture and capabilities across the whole organization (Ferraris, Mazzoleni, Devalle & Couturier, 2018). Big data analytic capability is the firm's ability to assemble, integrate, and deploy its big-data specific resources. To build big data analytic capability (BDAC), the firm needs a combination of tangible, human, and intangible resources (Gupta & George, 2016). The unique blend of financial, physical, human, and organizational resources that create the capability, will be difficult to match by competitors (Gupta & George, 2016). Previous research also shows that building capabilities will give firms a competitive advantage (Gupta & George, 2016) and developing their BDAC will increase their performance (Ferraris et al., 2018).

After reviewing the previous research, we decided to follow the framework provided by Gupta & George (2016) to determine the variables concerning BDAC. These include the tangible resources which is data, technology and basic resources. The intangible which is organizational learning and data-driven culture and human resources that are divided into managerial skills and technical skills. These will be defined in the section that follows.

2.2.1 Tangibles resources

Research based theory points at tangible resources as resources that can be bought or sold in a market (Gupta & George, 2016). This includes physical assets (e.g. equipment) and financial resources (e.g. equity) of the firm. Several of these kinds of resources are available to all other firms as well, especially if they are the same size and market. Therefore, tangible resources often do not provide any competitive advantage on their own but are often needed to create value or capabilities.

Data
To develop BDAC, accessibility to data is crucial (Gupta & George, 2016). Data has been used in decision making for a long time, but previously the data used was only enterprise-specific structured data that is created by the firm’s internal operations (e.g. inventory update, transactions, sales etc.), but today organizations tends to use every data that they can use, regardless of size and structure of the data (Gupta & George, 2016).

It has been identified five sources of data: public data, private data, data exhaust, community data, and self-quantification data (Gupta & George, 2016). Public data refer to government-owned data that are free. Private data refers to data generated, collected and owned by private firms. Data exhaust is defined as data that has no value attached to itself, but combining it with other types of data sources, it generates value (e.g. internet searches, location data). Data generated by users in different contexts such as social media, blogs etc. are referred to as community data. The last source of data, self-quantification data refers to data that is generated through technologies such as smart watches and other smart technology. These are often wearable technologies.

Overall, data is often categorized as internal data and external data. As mentioned, previously the data that were used in decision making were often enterprise-specific structured data. This type of data is considered to be internal data. External data is data that is generated outside of the firm such as customer information, social media generated data, mobile phones and sensors. Both internal and external data has to be considered and integrated if a firm is interested in creating BDAC.

Technology
The traditional use of technology regarding data has often been relational database management systems (RDBMS). This has previously been used to store structured data. But according to Gupta & George (2016), up to 80% of an organization’s data is unstructured data which forces organizations to move away from the traditional RDBMS methods of storing and analysing data. This has led to the need of databases that can store unstructured data, which led to the emergence of technologies to support these types of data sets which are known as NoSQL (not only SQL). Technology has often been considered an important factor to get competitive advantage in the market, but due to transparency and labor force mobility, the technology itself is often no longer a unique factor for competitive performance and the big data technology used in organizations often gets known to competitors (Gupta & George, 2016). Though technology itself is not often used as a competitive weapon, it is still an important factor for BDAC, where it is required to harvest the potential of big data.

Basic resources
Investment and time is considered to be a tangible resource that is required to create BDAC. This has been labeled as basic resource to differentiate these resources from the other resources and is an important factor besides technology and data.

2.2.2 Intangible resources

Intangible resources are considered central to a firm's performance, especially in dynamic markets, which big data is (Gupta & George, 2016). Intangible resources are not documented on firms’ financial statements, this is because they don't have clear and visible boundaries, and their value is highly context dependent. Intangible resources are usually not easily tradable in the market, however some exceptions such as trademarks, copyrights, and other intellectual capital (e.g. patients), can be sold or bought legally by organizations. Organizational learning and data-driven culture are two resources that firms should include and look for when trying to reap benefits from big data (Gupta & George, 2016).

Organizational learning
Organizational learning is the process through which firms explore, store, share, and apply knowledge (Gupta & George, 2016). The intensity of organizational learning will affect how firms have the ability to reconfigure their resources according to the changes

in their external environment, which will lead to a sustained competitive advantage. Though knowledge does not wear out, it may become outdated due to the emergence of new technologies or inventions (Gupta & George, 2016). Therefore, firms need to make concerted efforts to exploit their existing knowledge and explore new knowledge to cope with uncertain market conditions. Firms that manage to have high intensity of organizational learning are likely to have stocks of organizational knowledge that can be used toward creating BDAC. These stocks of knowledge can be combined with the insights extracted from big data to make informed decisions.

Data-driven culture
Data-driven culture is defined as the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data (Gupta & George, 2016; Ross, Beath & Quaadgras, 2013; McAfee & Brynjolfsson, 2012). The research on big data asserts that while organizations in all industries are collecting hordes of data, only a small percentage of organizations have actually benefited from their big data analytic investments. This is because most organizations rely on past experience and/or intuition of their top executives to make important decisions, which is commonly referred to as the highest paid person's opinion (Gupta & George, 2016). To realize the full potential of data owned by firms, it is critical that firms develop a data-driven culture (Gupta & George, 2016; Duan, Cao, Edwards, 2018; Cao & Duan, 2015). Employees at all levels in an organization are required to make some decisions, regardless of their job titles and have the ability to make good decisions that are grounded on some tangible evidence as suggested from data (Gupta & George, 2016).

2.2.3 Human skills

employees are likely to have some advantage over their rivals (Gupta & George, 2016). Gupta & George (2016) points at two dimensions as important aspects of a firm's human resources regarding BDAC. These are managerial skills and technical skills.

Managerial skills
Managerial skills are very firm-specific and is a result of individuals working in the same organization over a long period of time (Gupta & George, 2016). These skills are developed by individuals that have a strong interpersonal bond with other individuals in the same organization in various departments (Gupta & George, 2016). This type of skill lead to managers to have the knowledge to know where and how to apply insights that is extracted by the technical teams. These managers should be able to predict future needs, as well as understanding the current needs (Gupta & George, 2016).

Technical skills
Technical skills refer to the know-how required to use new forms of technology to extract intelligence from big data. Some of these skills include competencies in machine learning, data extraction, data cleaning, statistical analysis, and understanding of programming paradigms such as MapReduce. At this time, there are still a significant shortage of individuals with big data-specific technical skills (Gupta & George, 2016). Big data technology and the skills associated with it are still relatively new, resulting in organizations that have big data-skilled

2.3 Firm performance

Companies that are more concerned with being data-driven experience better performance on objective measures of financial and operational results (McAfee & Brynjolfsson, 2012; Ferraris et al., 2018). The main objective of collecting and analysing data is to develop actionable insights and new knowledge to establish competitive advantages, showing that big data analytics is becoming a major differentiator between high performance and low performance (Ferraris et al., 2018). In order to get the full performance increase from big data analytics, one also need to change the decision-making culture in the organization (Frisk & Bannister, 2017). We have divided firm performance into three dimensions; Social performance, market performance and competitive performance.

2.3.1 Social performance

Due to the rise in demand of social responsibility, organizations have been met with several challenges (Dubey, Gunaasekaran, Childe, Papadopoulos, Luo, Wamba & Roubaud, 2017). This is due to the increasing number of outsourced manufacturing jobs which is often directed towards low-wage countries. This is often connected to environmental issues such as working conditions (Mueller, Dos Santos & Seuring, 2009).

In the context of big data analytics, previous studies have suggested that big data analytics have a positive impact on social performance, and even imply that big data analytics is one of the organizational capabilities that assist organizations in improving their social performance (Dubey et al., 2017). Though this is mostly theoretical, the recent study by Dubey et al. (2017), suggest that there is evidence for a positive relationship between big data analytics and social performance.

2.3.2 Market performance

Market performance is covering to what extent an organization attracts and retains its customers for its products and services (Hogan & Coote, 2014).

2.3.3 Competitive performance

A firm is said to have a competitive performance when it enjoys greater success than current or potential competitors in its industry (Peteraf & Barney, 2003). Having a superior firm performance, relative to rivals indicates that an organization has a competitive advantage (Schilke, 2014). With the use of big data analytics an organization have the ability to collect more accurate and detailed performance data, this can be used to pinpoint issues and boost performance (Grover, Chiang, Liang & Zhang, 2018). There is however a gap between the big data analytics investments and the ability to effectively derive business insights and increase performance (Carillo, Galy, Guthrie & Vanhems, 2018).

3.0 Conceptual model and hypotheses

The research model was created and based on our systematic literature review and research question. The model represents the relationships between key constructs in our research area. Hypotheses was formulated to explain the connection between the variables in the model. The following sections describe the model and theory in detail.

3.1 Conceptual model

The model was developed by using elements gathered from the research in our systematic literature review. By using elements from established principles, we would ensure the quality and also make it easier to understand and more recognizable to the field. We designed a model in the beginning of the project that was continually updated and adapted as our knowledge in the field grew. This was done to make sure our model matched and could build upon prior work in the field. To increase the reliability and validity of our model, we implemented our own empirical work. Figure 1 shows our conceptual model.

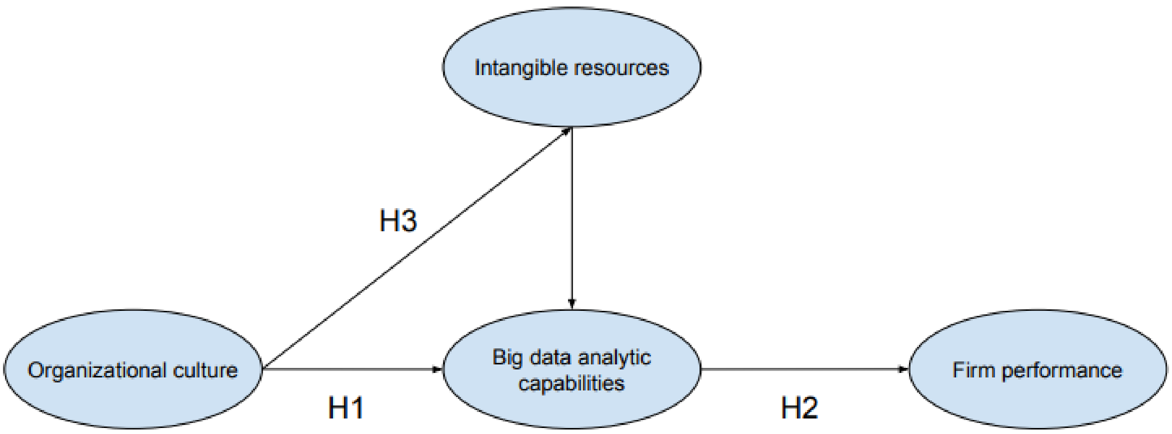

Figure 1: Conceptual model

3.2 Hypothesis

After developing our model, we formulated three hypotheses. The three hypotheses were developed to test if there was a positive effect between the various elements of the model. The three hypotheses are presented in the section below.

Hypothesis 1
Many barriers related to big data is cultural, rather than technological (Alharti et al. 2017). The goal of a big data investment is to enhance the organization's ability to make better decisions along with better decision execution processes. Making informed decisions is one of the building blocks of organizational success (Tabesh, Mousavidin & Hasani, 2019). All organizations that have put effort and investment in big data should be able to harvest results via gaining a competitive advantage and improving their performance. However, to fully harness the potential of big data, the organization also have to develop, nurture and maintain an organizational culture which will have a positive impact on their use of big data (Nguyen, 2018). This is important when around 80% of businesses have failed to implement their big data strategies successfully (Tabesh, 2019) and regardless of their efforts, many organizations have not been able to realize the potential of big data in an effective manner (Mazzei & Noble, 2017).

This resulted in the following hypothesis:

H1: “Organizational culture has a positive effect on big data analytic capabilities”

Hypothesis 2
Previous studies argue that big data itself does not give a competitive advantage, but rather developing capabilities that competitors struggle to match (Gupta & George, 2016). Creating BDAC, a combination of certain tangible, human and intangible resources can lead to superior firm performance. Studies also examine technology management and suggest that it is related with big data decision making, while technological competency is required to facilitate the use of big data for analysis (Shamim et al., 2018). One of the defining features of big data is the unsuitability of existing processing techniques and how to store large amounts of data to generate value from big data technology (Comuzzi & Patel, 2016). To generate value from big data and the technology used, organizations have to develop or acquire analytic capabilities, which allows the organization to transform data to valuable information (Thirathon, Wieder, Matolscy & Ossimitz, 2017). Dubey et al. (2019) argues that organizational capability development is needed to fully exploit analytic capabilities. Furthermore, the complementary capability development highly depends on the organizational culture. Even though the analytic and technical capabilities are developed within an organization, executives still struggle to understand and implement big data strategies effectively (Thirathon et al., 2017).
This resulted in the following hypothesis:

H2: “Big data analytic capability has a positive effect on firm performance”

Hypothesis 3
Gupta & George (2016) defines organizational learning as: “a process through which firms explore, store, share and apply knowledge”. Organizational learning opens up the opportunity for employees to exploit the existing knowledge and expand their knowledge to adopt and compete in a continuously changing market (Pappas et al., 2018). By reconfiguring the resources according to the changes in the external

environment, the organizations have better odds of having a sustained competitive advantage (Teece, Pisano & Shuen, 1997). To gain a competitive advantage, the intangible resources, such as data-driven culture and organizational learning is just as important as the tangible resources, where the insights extracted from data ought to be valued and acted upon (Gupta & George, 2016). Côrte-real, Ruivo, Oliveira & Popovic (2019) argues that organizations need to align their culture with a data-driven culture with a top-top approach, where strategy is a top priority.
This resulted in the following hypothesis:

H3: “Organizational culture has a positive effect on Intangible resources”

4.0 Research method

This chapter will explain the methods that was used in gathering and analysing the data from the survey. Based on this analysing, we will we answer the research question.

4.1 Research approach

The research question we developed is best answered by using a quantitative approach. We decided to use an extensive research design where we focused on several respondents with relatively few variables. This is a deductive study and by completing the systematic literature review, we established the hypotheses based on theoretical knowledge. This approach is a suitable approach for collecting empirical data, which can then be used to answer the hypotheses and our research question.

4.1.1 Survey

The survey was the main source of empirical data in order to answer our research question. The survey aims to obtain data from several respondents within our set population with a systematic approach. By reaching many different respondents within the given population, we will look for statistical patterns and aim towards generalizing the results for the population.

4.2 Research design

The research design shows the procedures we followed in order to get data to answer the research question. Our plan was in three phases, where we started to investigate the literature within the field. We completed a systematic literature review to make sure we had the complete knowledge within the topic of interest before starting to build conceptual model and collecting data. The next phase was the conceptual model development and developing the survey, while defining the population and gathering contact information to different companies that fit our population. We ended phase two by sending out the surveys. The last phase was used to send reminders to the organizations that did not answer the survey, as well as contacting more respondents via phone and social media to make sure the number of respondents was within our goal. After we had collected enough data, we started with data analysis. The report was gradually developed simultaneously with the different phases of our work. The complete research design is illustrated in figure 2.

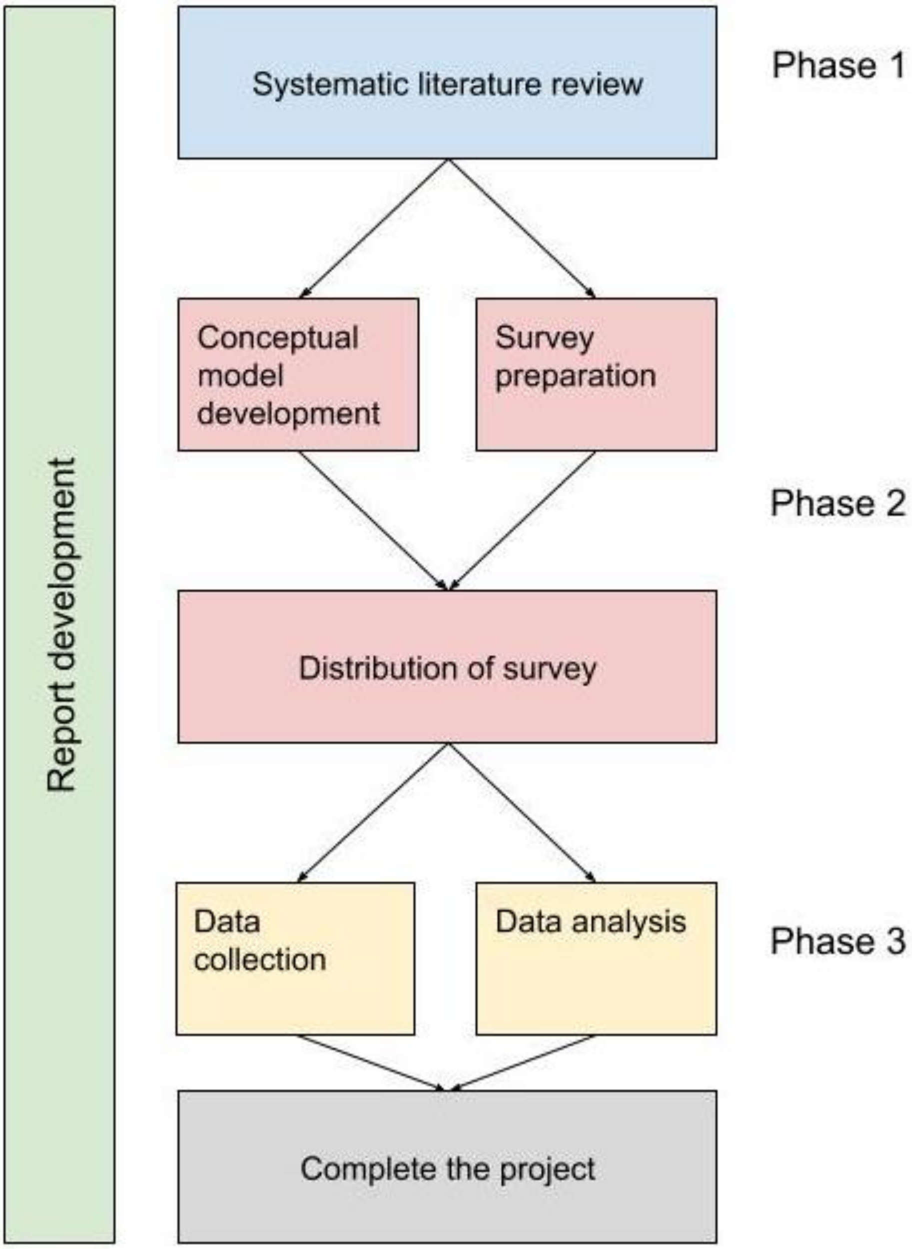

Figure 2: Research design

Project timeline
The first meeting with our supervisor, we developed a timeline. Due to our uncertainty about the required time used on the different phases, our supervisor helped us develop a timeline. In this timeline, we focused on setting specific milestones which we should reach at a certain time. The main result of this timeline was that we could always see progress throughout the project and did not procrastinate in any of the phases. The timeline also contributed to ensure that we had enough time for quality assurance and reviewing the report. The timeline we used is presented in figure 3

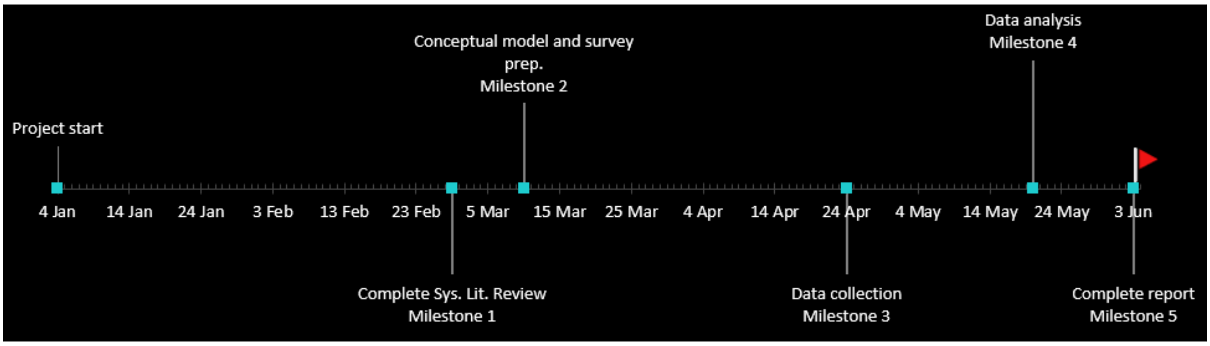

Figure 3: Project timeline and milestones

4.3 Preparation and model construction

For us to develop the conceptual model, we conducted a systematic literature review. In this section, we explain the process and procedures we used for the literature review. After the literature review, a description of how we operationalized the concepts and how we ensure the reliability and validity to the survey is presented.

4.3.1 Systematic literature review process

Reviewing previous literature is a key element in any academic work. The benefits of performing a systematic literature review is that it provides a framework/background in order to position new research activities (Kitchenham & Charters, 2007). There is an overwhelming amount of literature on this topic and reviewing this will be difficult. By using a systematic approach to review the literature, we ensure that the quality will be higher and the process of reviewing the literature in a good manner will be achievable. By using this approach, it makes it less likely that the chosen literature is biased (Kitchenham & Charters, 2007).

There are several ways of conducting a systematic literature review. Our literature review is based on the guidelines presented by Webster & Watson (Webster & Watson, 2002). The process that has been used in this review is documented in the next section.

When searching for relevant literature regarding our research question, we used seven databases. The databases we used were Wiley Online Library, SAGE journals, Taylor & Francis Online, Emeraldinsight, IEEE Xplore digital library, Sciencedirect and Scopus. By differentiating the use of databases, we ensure to obtain the literature required to perform a proper systematic literature review. In these databases, we used several search strings which included synonyms and other phrasing of the constructs used in the research question. The keywords used in the searches were not limited to title or abstract, but rather everywhere in the article. The phrases we decided to use were carefully selected by looking at different possibilities and synonyms that might increase the search result. This resulted in four different search strings which is presented in table 2.

By using a different set of search strings presented in table 2, we ended up with a plethora of gathered literature. The search strings we used, the total amount of articles for each search string and the number of articles that were used in systematic literature review is presented in table 2.

Search strings	*Results*	*Used articles*
"Analytic Culture"	384	1
"Big Data" AND "Organizational Culture"	1455	10
"Data Analytics" AND "Organizational Culture"	817	1
"Data-Driven Culture"	218	7
Total results	2874	19

Table 2: Search strings and results

Selection process

The literature was manually reviewed to conclude the relevance to this study by reviewing the title, abstract and full text and compare it to our research question. Therefore, we developed some inclusion and exclusion criteria for this review to assist us in evaluating the relevance of the articles to our research question and literature review. The articles that met the requirements in the inclusion criteria were used in the primary studies. The articles that included the exclusion criteria, were not used in the study. The inclusion and exclusion criteria are shown in table 3.

Inclusion criteria	*Exclusion criteria*
Conference proceedings	Mentioning terms, but not related to our RQ
Focus on big data and relates to the RQ	Not peer-reviewed journals/conferences
Peer-reviewed journal	Books

Table 3: Inclusion and exclusion criteria

The approach for gathering the literature were based on a concept centric approach, were we reviewed the concepts of the articles in relation to our research question. By using this approach, we eliminated several articles that had the search strings in their title or abstract but were not relevant to our study because of the wide range of research regarding these topics. We did not exclude "lower quality" journals because literature that is published in journals assumed to have less quality, may have established some new research that might assist this research in a positive manner. Watson & Webster (2002) states that a literature review should not confined to one research methodology, one set of journals or one geographic region. By having this approach, we manage to look at literature that might not be published in the "top" journals but might have some contribution to the topic of interest.

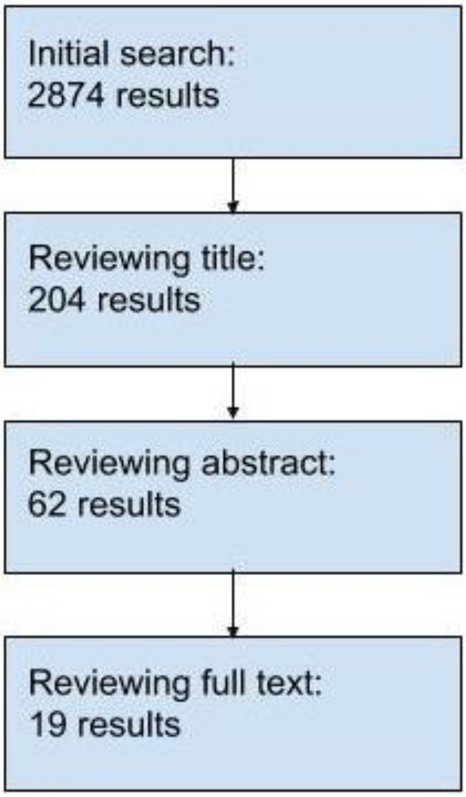

Figure 4: Article collection process

By reviewing the titles of these articles, we looked at the relevance they had to our topic and research question. In this phase, we were open to articles that were not directly connected to our research question and accepted them when they were somewhat relevant. This was to ensure that we did not exclude any articles too soon. Figure 4 shows the process of choosing the articles.

In addition to these 19 articles, we rounded up the process by searching Google Scholar to see if there were any papers that were relevant to our systematic literature review that might not show up in the other searches. In this search process, we managed to find two papers that had a direct connected to our topic that we decided to include in this paper. The articles we included were Mikalef et al. (2017) and Pappas et al. (2018).

4.3.2 Findings

The findings of this literature review is presented in two parts. The first part is presented quantitatively. The year of publication for each article is illustrated in figure 5.

The second part is analysing and interpreting the data from the selected studies to answer the research question. The main concepts discussed in the articles are big data and organizational culture. The different dimensions of both of these concepts are being discussed in the literature, however the level of focus on each paper varies. The majority of the papers mentions organizational culture as an important factor in big data adoption, but few of them have organizational culture as a primary focus. The remaining papers that does, contribute more to the field of organizational culture, were they have more focus on the cultural part, even though it is in the context of big data. When analysing the literature, we discovered that there were many challenges and sometimes solutions being presented in the articles. To make this a useful contribution, we decided to divide this into challenges and strategies for overcoming these.

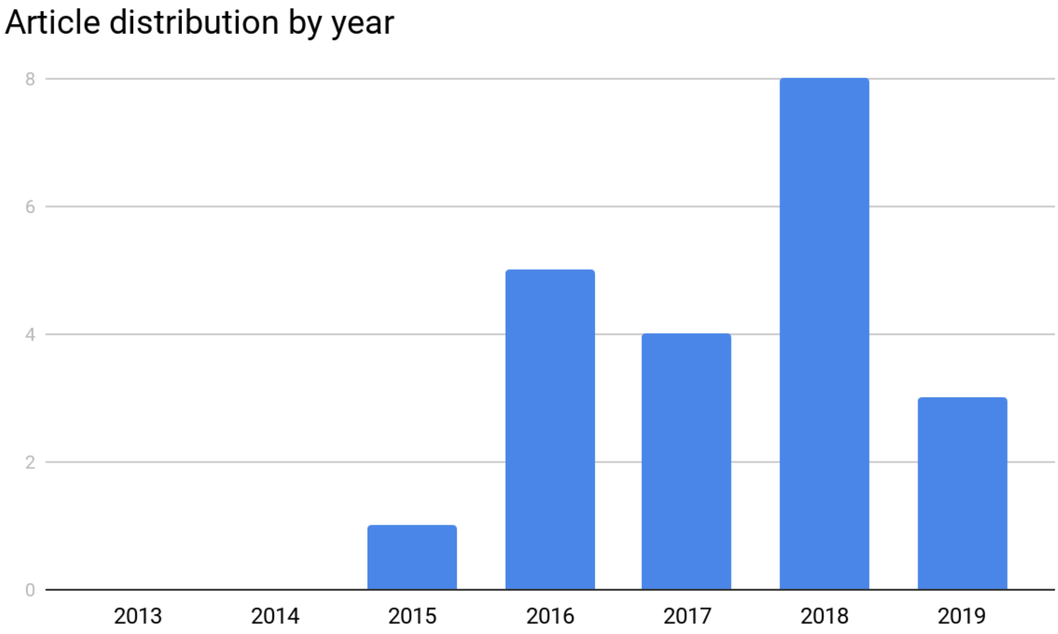

Figure 5: Articles distribution by year

4.3.3 Concept matrix

The concept matrix was developed to get a figure that illustrate the concepts discussed in the literature.

	Big data				Organizational culture		
Articles / Concepts	Technology management	Big data analytics capabilities	Big data management capabilities	Big data analytic strategy	Assumptions	Artifacts	Values
1. Alharthi et al., 2017	X			X		X	X
2. Dubey et al., 2019		X	X		X		
3. Ferraris et al., 2018			X				X
4. Thiraton et al., 2017		X	X				X
5. Dubey et al., 2017	X		X				X
6. Ylijoki & Porras, 2016							X
7. Grover et al., 2018			X	X	X	X	
8. Comuzzi & Patel, 2016			X	X			
9. Carillo et al., 2018			X				X
10. Jeble et al., 2018	X	X	X		X	X	X
11. Frisk, 2016		X	X	X	X		X
12. Shamim et al., 2018	X				X	X	X
13.Nguyen, N. 2018				X	X	X	X
14. Gupta & George, 2016	X	X	X		X		X
15. Adrian et al, 2016			X	X		X	
16. Côrte-real et al., 2019	X	X	X	X		X	X
17. Mikalef et al., 2017		X		X	X	X	X
18. Pappas et al., 2018		X			X		X
19. Tabesh et al., 2019	X	X		X		X	X
20. Cao & Duan, 2015	X	X				X	X
21. Duan et al., 2018	X		X	X		X	X

Figure 6: Concept matrix

4.3.4 Organizational culture's impact on big data adoption

Organizational culture through its assumptions, values, norms, and symbols has a strong impact on various aspects of an organization, such as strategy, structure, and processes (Alharti et al., 2017). This can be related to many of the obstacles that form when an organization is trying to adopt big data. These obstacles are likely to be related to organizational culture and not to data or technology (Alharthi et al., 2017). Recent literature acknowledges this by expressing that organizational culture has a critical role in the success of big data initiatives and is often the main reason why big data initiatives fails, rather than technological factors (Shamim et al., 2018; LaValle, Lesser, Shockley & Hopkins, 2011; Adrian, Abdullah, Atan & Jusoh, 2016). Some go as far as saying that the main challenges for big data management is the organizational culture (McAfee & Brynjolfsson, 2012; Shamim et al., 2018). This means that the impact big investments has on an organization is usually driven by the culture and not the big data investment itself (Thiraton et al., 2017; Grover et al., 2018), requiring that business analytics must become part of the organizational culture and all employees have to have a positive attitude towards it (Müller & Jensen, 2017).

4.3.5 Challenges of organizational culture in big data adoption

Most of the literature brings up several specific cultural challenges when adopting big data. The next section will report the identified challenges.

In a continuously changing environment, the ability to adapt and reconfigure the resources accordingly is crucial for organizations to maintain a competitive advantage (Gupta & George, 2016). One of the aspects that influences this ability is organizational learning. Organizational learning refers to the organization's ability to explore, store, share and apply knowledge (Grant, 1996; Bhatt & Grover, 2005). Due to the rapidly changing market conditions and innovations of new technologies, such as big data, the organizations are challenged to become more agile and adapt to the ever-changing market (Gupta & George, 2016). Another challenge that is presented is that the organizations need to adapt their organizational culture and adopt new procedures of organizational learning in order to benefit from big data.

Management challenges that may prevent companies from succeeding in big data initiatives include leadership and strategy (McAfee & Brynjolfsson, 2012). Having top management support (LaValle et al., 2011; Halaweh & El Massry, 2015) and appropriate technical and management skills (Waller & Fawcett, 2013) is also important when trying to acquire success with big data initiatives. The behaviour of top managers that does not value data-driven decision making, will affect the decision patterns at all levels of the organization (Tabesh et al., 2019). Obtaining full benefits from big data does also require aligning existing organizational culture and capabilities across the whole organization (Ferraris et al., 2018). This can be a challenging task for the management. Overcoming leadership focus, harnessing talent, technology management and company culture (McAfee & Brynjolfsson, 2012), which are even bigger contributing factors than the technical ones (Shamim et al., 2018), does also present a challenge. Concluding with the words of Gupta & George (2016): “the intelligence gleaned from data will be of little use to an organization if its managers fail to foresee the potential of newly extracted insights”.

A data-driven culture is defined as “the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data” (Gupta & George, 2016). The lack of data-driven culture is among the major reasons for the high failure rate of big data projects (Ross et al., 2013). The organizations face the challenges of developing a data-driven culture that manifest a view of data-driven decision making as valuable to decrease the chance of resistance to the development of data-driven culture in order to benefit from big data. Further, developing a data-driven culture requires the management to base their decisions on data, rather than instinct (Dubey et al., 2017) and change their attitude towards data-driven decision making (Ylijoki & Porras, 2016). This leads to the several challenges suggested by Ylijoki & Porras (2016), where this challenge often requires the whole organizational culture to change as well as the decision-making process. The organizations ought to change the decision-making process for all members of an organization, including lower-level employees, middle-level managers and top-level executives (Gupta & George, 2016).

4.3.6 Strategies for combating the barriers with big data adoption

A number of strategies, techniques, requirements and suggestions to overcome these challenges are presented in the literature and identified in this study.

In regard to organizational learning, Bhatt & Grover (2005) and Teece (2015) argues that organizations need to make concerted efforts to use their existing knowledge to explore the new knowledge that is aligned with the changing market. Based on this knowledge, organizations can combine it with insight extracted from big data to generate value (Gupta & George, 2016). Shamim et al. (2018) also points at the importance of developing a culture that is strongly change-oriented in order to utilize organizational learning.

First an organization needs to create and foster an organizational culture that is supportive of fact-based decision making and big data analytics. Developing a clear vision of how big data fits with the overall strategy of an organization should help accelerate and solidify the acceptance of this type of organizational culture. Once the vision is formulated, it has to be translated into specific organizational processes and initiatives that rely on big data to improve organizational performance (Alharthi et al., 2017). Successful cultural change of this nature can be achieved by documenting, implementing, and communicating a clear organizational vision in relation to big data ensuring top management commitment to this vision, and managing the drivers that influence organizational culture rather than trying to manage culture itself (Rogers, Meehan, & Tanner, 2006). Adopting a design approach is also a way of enabling organizations to change their decision-making culture and increase the collaboration between different actors and Frisk (2016) points at the influence of organizational culture in this process. Further, Côrte-real et al. (2019) argues that organizations need to align their culture with a data-driven culture with an top-top approach, where strategy is top priority. Then it is followed by managerial and operational factors. A culture that embraces data- and evidence-driven approaches to business decisions, and governance that delineates responsibility and accountability for data, are both catalysts for big data analytics value creation (Grover et al., 2018).

Prior studies in management strategy have identified organizational culture as a source of sustained firm performance (Barney, 1995; Teece, 2015; Barney, 1986). Developing top management support is one of the critical success factors of big data implementation (Halaweh & El Massry, 2015). Commitment and support among management can significantly mitigate the cultural and technological barriers to big data strategies. This is done by commitment to big data projects that facilitates in generating a data-driven culture by sending signals to everyone in the organization (Adrian et al., 2018). Managers should also build multi skilled teams consisting of data scientists, engineers with technical knowledge and translators who are familiar with both technical and business languages. This can help managers interpret the generated insights before transforming them into business decisions (Mayhew et al., 2016). This practice can over time create a rich culture of open communication that will help addressing big data challenges (Tabesh et al, 2019). Further, aligning the existing organisational culture and capabilities across the whole organization (Ferraris et al., 2018) is another one. Companies must not only hire scientists who can translate big data into useful business information in order to have success. There is also a need of change in the managerial mindset, re-orient it to having a more digital and data-driven culture focus (Ferraris et al., 2018). Managers must also "attend to the big data era" (Mishra, Luo, Jiang, Papadopoulos & Dubey, 2017), resulting in becoming skilled in its methods and analytics, and learn to explore big data to develop the needed competitive advantage. Companies that manage to develop leadership teams with clear big data strategies, have clear goals, and can articulate the business case, would increase the likelihood of succeeding. Those teams can define what success is and have the ability to ask the right questions (Grover et al., 2018).

4.4 Construct Definition and Measures

In order to answer our research question and hypotheses, we had to develop questions that measured the right variables. There are a lot of well-established operationalization of the variables in previous literature. Our systematic literature review contained these operationalizations and the questions we are using are found in previous surveys and research papers. We started to make a list of all the questions that were measuring each of our variables, then we evaluated the different questions. The chosen questions were then sent to the supervisor for confirmation to make sure we had the right questions to measure our variables.

Operationalization of control questions

We developed a few introductory questions in order to collect different demographic information to support the study. The first question that we asked is if the respondents used big data in their organization. It is important to make sure the respondents are using big data before continuing the survey. We also used a question to determine the organizations company size. This is measured in the number of employees. To address the firm size, we measured it as an ordinal value in accordance with the European Commission's recommendations into micro (0-9 employees), small (10-49 employees), medium (50-249 employees) and large (> 250 employees) (Mikalef et al., 2019). The size of the organization will provide us with good background information to extend our findings. We also had a question regarding the organization type (e.g. private, public, profit or nonprofit). Other background information was gathered through the last three questions where we asked about the respondent's role in company, country of residence and type of industry. The last two questions were free text, where they could explain what industry they worked in with their own words. These questions may also help extending the findings. The questions are shown in table 4.

Name	Questions
IN1	Do you use big data in your organization?
IN2	Type of company
IN3	Company size (number of employees)
IN4	Country of residence
IN5	What type of industry do you work in?

Table 4: Operationalization of introductory questions

Operationalization of organizational culture

As stated in chapter 2, the fundamental levels of organizational culture presented by Schein provided the three constructs of organizational culture. Hogan & Coote (2014) provided the dimensions necessary to measure organizational culture, and these were attached to the different levels formulated by Schein (1990). Organizational culture is therefore divided into artifacts, value and assumptions (Nguyen, 2018). Artifacts consists of appreciation of employees, inter-functional co-operation and success. Values consists of risk-taking and competence and professionalism. Assumptions consists of openness/flexibility, internal communication and responsibility. The whole construct is shown in Figure 7.

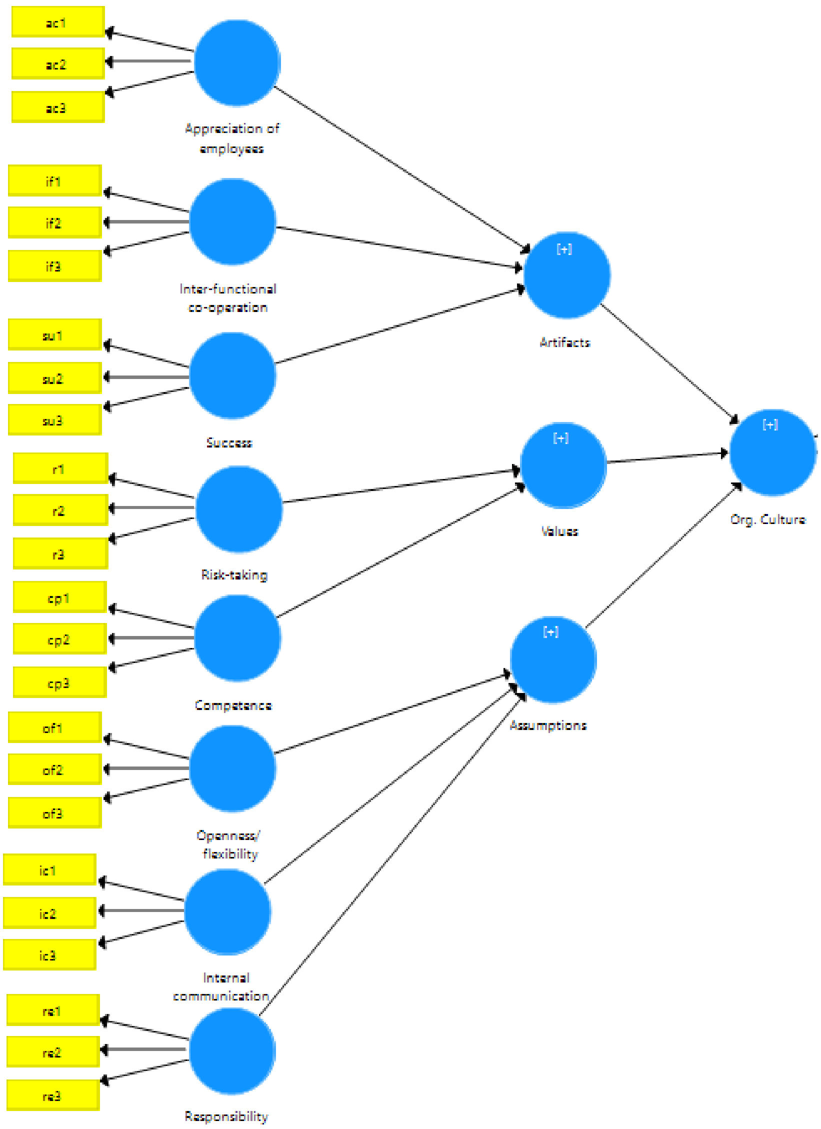

Figure 7: Third order construct of organizational culture

Assumptions
The three dimensions measuring assumptions and the questions are provided below.

Openness and flexibility are referring to the degree organizations values openness & responsiveness to new ideas (Hogan & Coote, 2014). Additionally, it is to the degree to which organizations provides and facilitates flexible approaches to solving the problems. This item measures the organization's ability to be forthcoming towards the new ideas and assist the problem solving.

Internal communication refers to how much value is put upon open communication and to what degree the organization facilitates information flow (Hogan & Coote, 2014). This is because of social development theory that is emphasizing cognitive growth through communication of information. This item is used to measure to what degree organizations value open communication and has the technology and procedures to facilitate it.

Responsibility will cover how an organization value the proactiveness, initiative and responsibility their employees have for their work (Hogan & Coote, 2014). This will measure how an organization appreciate employees being proactive, taking initiative and taking responsibility for their work.

Name	Question	Source
Openness and flexibility	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
OF1	We value openness and responsiveness in this firm	(Hogan & Coote, 2014)
OF2	We place great value on being flexible in our approach to problems	(Hogan & Coote, 2014)
OF3	A willingness to show flexibility and openness in valued within this firm	(Hogan & Coote, 2014)
Internal communication	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
IC1	Open communication is valued highly within this firm	(Hogan & Coote, 2014)
IC2	We place great value on excellent internal communication within this firm	(Hogan & Coote, 2014)
IC3	Maintaining high quality internal communication is valued within this firm	(Hogan & Coote, 2014)
Responsibility	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
RE1	We place great value on every employee being proactive in his/her role	(Hogan & Coote, 2014)
RE2	The firm values employees using their initiative	(Hogan & Coote, 2014)
RE3	We value employees taking responsibility for their work	(Hogan & Coote, 2014)

Table 5: Operationalization of openness, internal communication and responsibilities

Values
The two dimensions measuring values and the questions are provided below.

Risk taking refers to the degree an organization values the employees' new ideas where they are challenging the status quo and experiments with new ideas (Hogan & Coote, 2014). This measures the organization's ability to value and support risk taking ideas.

Competence and professionalism are how an organization values knowledge and skills (Hogan & Coote, 2014). This is to measure how an organization value professional knowledge, skills and their attitude towards professionalism.

Name	Questions	Source
Risk-taking	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
R1	This firm values a willingness to challenge the status quo	(Hogan & Coote, 2014)
R2	This firm values a willingness to experiment with new ideas	(Hogan & Coote, 2014)
R3	Valuing calculated risk-taking helped this firm get to where it is today	(Hogan & Coote, 2014)
Competence and professionalism	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
CP1	We place great value on professional knowledge and skills	(Hogan & Coote, 2014)
CP2	We aspire to a high level of competence and professionalism	(Hogan & Coote, 2014)
CP3	Upholding the highest levels of professionalism is valued within this firm	(Hogan & Coote, 2014)

Table 6: Operationalization of organizational culture

Artifacts
The three dimensions measuring artifacts and the questions are provided below.

Inter-functional co-operation is very important in big data, where this item measures the degree an organization values coordination and teamwork. Hogan & Coote (2014) argues that this is crucial in innovative projects where members from different functional areas working together with another specialist will increase the positive outcome.

Appreciation of employees is crucial and displays how an organization recognize the contribution of their employees, especially towards organizational goals and showing them respect (Hogan & Coote, 2014). This will be measured by recognizing employees' accomplishments, celebrate them and showing appreciation for their efforts.

Success is to what extend an organization strives for success and the highest standards of performances (Hogan & Coote, 2014). Having a clear organizational goal is important for the success of the organizational culture (Grover et al., 2018). Success will be measured in how an organization values success within the firm, their aspirations to be the best firm in their respected market and the value they place on performance.

Name	**Questions**	**Source**
Inter-functional co-operation	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
IF1	Cooperation among different work teams are valued highly	(Hogan & Coote, 2014)
IF2	This firm values integration and sharing among teams throughout the firm	(Hogan & Coote, 2014)
IF3	We place great value on co-coordination among different work teams	(Hogan & Coote, 2014)
Appreciation of employees	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
AC1	We place great value on recognizing and rewarding employees' accomplishments	(Hogan & Coote, 2014)
AC2	Taking time to celebrate employee's work achievements is valued in this firm	(Hogan & Coote, 2014)
AC3	We place great value on showing our appreciation for the efforts of each employee	(Hogan & Coote, 2014)
Success	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
SU1	We value success in this firm	(Hogan & Coote, 2014)
SU2	We aspire to be the best firm in our market	(Hogan & Coote, 2014)
SU3	We place great value on our performance	(Hogan & Coote, 2014)

Table 7: Operationalization of Inter-functional co-operation, appreciation of employees and success

Operationalization of big data analytic capabilities

The construct presented by Gupta and George (2016) provided a good basis for the big data analytic capability construct. They define big data analytic capability as a third-order construct and divided into human skills, tangibles and intangibles. We adopted this construct and it is shown in Figure 8.

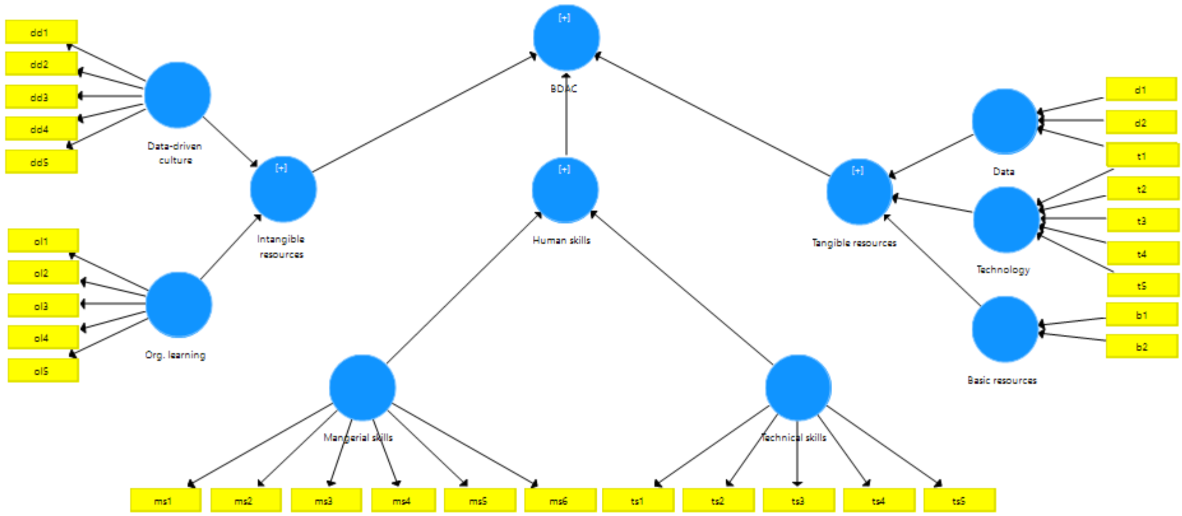

Figure 8: Third order construct of BDAC:

Tangibles

The tangible resources are divided into basic resources, data and technology. These assets can be sold or bought in a market (Gupta & Georg, 2016). They can be financial resources or physical resources. The questions are shown in table 8.

Basic resources include both time and investments (Gupta & George, 2016). This is done so that organizations can be measured for the strength of their concepts and basic resources when it comes to investing in big data initiatives and giving the investments enough time to grow.

Data is an important factor of production (Mitchell, 2014). This will measure what kind of access the organization has to data, how they manage to integrate the data from multiple internal and external sources.

Technology is about how the organizations that want to use big data analytics need to have some type of database management systems. This will be measured by how willing they are to explore or adapt different computing approaches, visualization tools, services, software and databases.

Name	Question	Source
Data	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	Gupta & George (2016); Jeble et al. (2018)
D1	We have access to very large, unstructured, or fast-moving data for analysis	Gupta & George (2016); Jeble et al. (2018)
D2	We integrate data from multiple internal sources into a data warehouse or mart for easy access	Gupta & George (2016); Jeble et al. (2018)
D3	We integrate external data with internal to facilitate high-value analysis of our business environment	Gupta & George (2016); Jeble et al. (2018)
Technology	We have explored or adopted ____ (1- totally disagree, 7- totally agree)	Gupta & George (2016); Jeble et al. (2018)
T1	parallel computing approaches (e.g. Hadoop) to big data processing	Gupta & George (2016); Jeble et al. (2018)
T2	different data visualization tools	Gupta & George (2016); Jeble et al. (2018)
T3	cloud-based services for processing data and performing analytics	Gupta & George (2016); Jeble et al. (2018)
T4	new forms of databases such as NotOnlySQL (NoSQL) for storing data	Gupta & George (2016); Jeble et al. (2018)
Basic resources	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	Gupta & George (2016); Jeble et al. (2018)
B1	Our big data analytics projects are adequately funded	Gupta & George (2016); Jeble et al. (2018)
B2	Our big data analytics projects are given enough time to achieve their objectives	Gupta & George (2016); Jeble et al. (2018)

Table 8: Operationalization of basic resources, data and technology

Human resources

The human resources of an organization consist of its employees' experience, knowledge, business acumen, problem-solving abilities, leadership qualities, and relationships with others (Gupta & George, 2016). We adopted technical skills and managerial skills as these are important aspects of an organization`s big data resources (Gupta & George, 2016): The questions are shown in table 9.

Technical skills allude to the know-how required to use new forms of technology to extract intelligence from big data (Gupta & George, 2016). The measurement of technical skills will paint a picture of how well an organization rate when it comes to providing and owning the skills to perform big data analytics with success.

Managerial skills play an important role in the intelligence extracted from the data (Gupta & George, 2016). If managers fail to see the potential that can be gained from the data, it will be of little use to the organization (Gupta & George, 2016). It is therefore imperative for managers to have a sharp understanding of how and where to apply information that is being extracted by their technical teams (Gupta & George, 2016). Mutual trust and good working relationship between big data managers, and other functional managers has the potential of developing superior human big data skills that will be difficult for other organizations to match (Gupta & George, 2016). This will be measured by how the big data analytic managers understand and appreciate, able to work, coordinate, and anticipate the needs of other functional managers, suppliers, and customers.

Name	**Question**	**Source**
Technical skills	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	Gupta & George (2016)
TS1	We hire new employees that already have the big data analytics skills	Gupta & George (2016)
TS2	Our big data analytics staff has the right skills to accomplish their jobs successfully	Gupta & George (2016)
TS3	Our big data analytics staff has suitable education to fulfill their jobs	Gupta & George (2016)
TS4	Our big data analytics staff holds suitable work experience to accomplish their jobs successfully	Gupta & George (2016)
Managerial skills	Our big data analytics managers ____ (1- totally disagree, 7- totally agree)	Gupta & George (2016)
MS1	understand and appreciate the business needs of other functional managers, suppliers, and customers	Gupta & George (2016)
MS2	are able to work with functional managers, supplier and customers to determine opportunities that big data might bring to our business	Gupta & George (2016)

MS3	are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	Gupta & George (2016)
MS4	are able to anticipate the future business needs of functional managers, suppliers, and customers	Gupta & George (2016)
MS5	have a good sense of where to apply big data	Gupta & George (2016)
MS6	are able to understand and evaluate the output extracted from big data	Gupta & George (2016)

Table 9: Operationalization of technical skills and managerial skills

Intangible resources
Intangible resources are not documented on an organization's financial statements like tangible resources (Grant, 2016, p.128). The intangible resources are divided into two assets in relation to big data analytics; organizational learning and data-driven culture (Gupta & George, 2016).
The questions are shown in table 10.

Data-driven culture
Data-driven culture is the organization's ability to utilize data in their decision-making process. This is throughout the company, where lower-level employees, middle managers and top-level executives are basing their decisions on data, and not on their intuition (Gupta & George, 2016; McAfee & Brynjolfsson, 2012). Gupta & George (2016) also states that organizations that makes decisions influenced by the title of some individuals rarely manage to reap the benefits of big data investments. Our questions measure to what extent the organizations use data versus intuition when making decisions and how the organizations advocate the use of big data throughout the organization.

Intensity of organizational learning
Knowledge never wear out but may be outdated because of the new technologies (Nonaka & Teece, 2001) and organizations need to make a concerted effort to exploit their existing knowledge and explore and gain new knowledge (Teece, 2015; Bhatt & Grover, 2005). It is, therefore, arguably safe to say that firms with a higher intensity of organizational learning are more likely to benefit from the knowledge use it to create big data analytic capabilities (Gupta & George, 2016). We chose to use questions focused on the organization's ability to acquire new knowledge and how they utilize their existing competencies to gain value of the new knowledge.

Name	Question	Source
Data-driven culture	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	Gupta & George (2016)
DD1	We considered data a tangible asset	Gupta & George (2016)
DD2	We base our decisions on data rather than on instinct	Gupta & George (2016)
DD3	We are willing to override our own intuition when data contradict our viewpoints	Gupta & George (2016)
DD4	We continually assess and improve the business rules in response to insights extracted from data	Gupta & George (2016)
DD5	We continuously coach our employees to make decisions based on data	Gupta & George (2016)
Organizational learning	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	Gupta & George (2016)
OL1	We are able to search for new and relevant knowledge	Gupta & George (2016)
OL2	We are able to acquire new and relevant knowledge	Gupta & George (2016)
OL3	We are able to assimilate relevant knowledge	Gupta & George (2016)
OL4	We are able to apply relevant knowledge	Gupta & George (2016)
OL5	We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge	Gupta & George (2016)

Table 10: Operationalizing of data-driven culture and organizational learning

Operationalizing of firm performance

Firm performance refers to how an organization perform in different dimensions of performance. We have divided performance into three dimensions: Social performance, market performance and competitive performance. This construct is illustrated in figure 9.

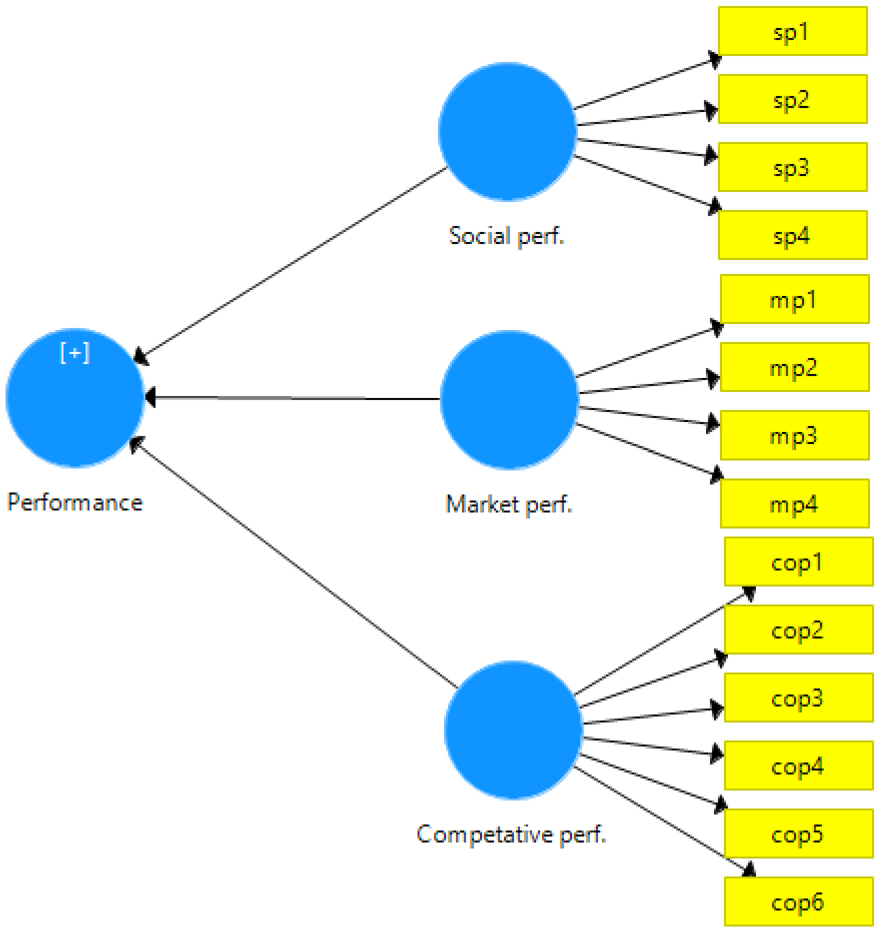

Figure 9: Second order construct of firm performance

Social performance

Previous studies have developed several designs to measure economic and environmental performance of the firms, but social performance has not been measured due to the intangible nature and complexity of the notion (Mani, Agrawal & Sharma, 2014). In developing countries, the social performance construct is often an issue, where organizations themselves develop and share their social responsibility report in order to create awareness surrounding this issue (Jeble, Dubey, Childe, Papadopoulos, Roubaud & Prakash, 2018). We included this construct to measure the social performance awareness in European companies and their focus on these issues. The questions we used is adopted from Jeble et al. (2018), where the questions are measuring the organizations gender equality, workers and their family's health, poverty and the level of nutritional focus.

Market performance
Market performance relates to how an organization attracts and retains customers for its services and products (Morgan & Piercy, 1998; Hogan & Coote, 2014). These four items measure the firm's ability to achieve client satisfaction, if the firm can keep their current clients and attract new clients as well as their desired growth.

Competitive performance
Competitive performance refers to what degree an organization is performing compared to their competitors. Measuring competitive performance is done by using six items that measures strategic advantage, market share, successfulness, EBIT (earnings before interest and taxes), ROI (return on investment) and ROS (return on sales).

Name	Question	Source
Social performance	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	Jeble et al., 2018
SP1	Our firm believes in gender equality	Jeble et al., 2018
SP2	Our firm pays significant attention to the mortality rate of the daily wage workers children	Jeble et al., 2018
SP3	Our firm believes in poverty reduction	Jeble et al., 2018
SP4	Our firm pays significant attention to the nutritional status of the meal served in the canteen	Jeble et al., 2018
Market performance	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	Hogan & Coote, 2014
MP1	Our firm is achieving client satisfaction	Hogan & Coote, 2014
MP2	Our firm is able to keep the current clients	Hogan & Coote, 2014
MP3	Our firm is attracting new clients	Hogan & Coote, 2014
MP4	Our firm is attaining desired growth	Hogan & Coote, 2014
Competitive performance	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	Schilke, 2014 (Hentet fra corte-real et al.)
COP1	We have gained strategic advantages over our competitors	Schilke, 2014
COP2	We have a large market share	Schilke, 2014

COP3	Overall, we are more successful than our major competitors	Schilke, 2014
COP4	Our EBIT (earnings before interest and taxes) is continuously above industry average	Schilke, 2014
COP5	Our ROI (return on investment) is continuously above industry average	Schilke, 2014
COP6	Our ROS (return on sales) is continuously above industry average	

Table 11: Operationalization of social, market and competitive performance

Questionnaire validity
Our strategy for developing the questionnaire was to see what other peer-reviewed articles did in order to make sure the measurements were tested and previously used. We also used our supervisor to review the questionnaire for quality insurance.

Content validity
The content validity was secured by using questions from the previous literature that was found during the systematic literature review and additional research. This ensured that the questions we used could accurately measure the different variables we had in our constructs. All the questions from the literature that measured the different variables was collected and evaluated before we selected the best ones. This was done in cooperation with our supervisor. After finalizing the survey, we were left with 67 questions.

Construct validity
To make sure we were measuring what we thought and wanted to measure, we used questions from the literature that was connected to their respective variables. By picking variables that was connected to the different constructs in the literature, and the ones we had in our model, we would increase the quality of the selected questions. We also examined the literature to see if they had any problematic encounters with their questions.

4.5 Method for collecting data

In this section, we explain the methods used in the study. Here we will go through the method used for the survey data collection and analysis and end with how we secured reliability and validity for the data analysis.

Population selection
When we were discussing how to find a suitable population, we looked at different characterizations the organizations had to meet. For us to be able to complete a statistical analysis of the collected data, we had to ensure we would get enough respondents. According to Hair, Black, Babin & Anderson (2014, p. 100), the number of

respondents should be at least 100, bear minimum 50. By discussing with the supervisor about the number of respondents to get a reliable statistical analysis, we ended up with a starting point of 100-200 respondents.

After discussing the acceptable number of respondents, we were looking into other demographics of our population. Due to the relatively new phenomenon regarding BDAC, we were aiming towards European countries. This is done because of the availability of the respondents and makes it more like that we get more respondents. Most of the respondents has been from Norway, due to our personal relationships to different organizations in various industries. Having a population that spreads across many borders may bring problems such as different contextual factors that may influence either the organizational culture, BDAC or performance construct. The countries of our respondents were mainly from Scandinavia and western European countries which arguably do not differ significantly in this topic and often have businesses across borders in the same regions.

The topic of this thesis focuses on BDAC, as well as organizational culture which is measurable in different levels of employment. This led to our target population being executives that manages big data solutions, as well as workers that are directly connected with their big data solution. The main requirement we set for the population is that their organization is actively using big data solutions, as well as the employee completing the survey has a significant role regarding their solutions (e.g. manager, data analysts etc.). These people were often within business intelligence departments or general IT-departments.

4.5.1 Data collection method

We primarily aimed at medium and large organization. This is because of the uncertainty in the size of the population, and problematic to figure out organizations which are actively using big data analytics. We had the assumption before starting to collect data that organizations actively using big data solutions would feel a responsibility to help students conducting research in a field where they actively part take in. This assumption is based on previous experience where organizations have been forthcoming regarding university projects and research. In order to find organizations that were using big data solutions, we turned to our personal relationships with friends and family that might have connections to people that are competent to answer the survey. In addition to personal communication, we also used target search on social media platforms such as LinkedIn and Facebook. We also used several big data groups on the mentioned social media platforms in order to reach more people. After collecting several potential respondents, we simply used a spreadsheet with contact person, organization name and contact information in order to systematically contact them.

We started by contacting these organizations through e-mails and experienced very low respondent rate. The respondent rate of the first distribution was approximately 2-3% which was a little unexpected. We sent out one additional reminder. We did not get as many respondents as we needed, which resulted in contacting the respondents by phone. This was a very resource effective method where the respondent rate was significantly higher than by e-mails and the organizations had a positive feedback on our survey. We also used direct messages on social media platforms such as LinkedIn and Facebook. Additionally, we used snowball sampling techniques (Oates, 2006, p.98) were we asked the respondents that agreed to take the survey to distribute the survey to other potential organizations that are using this technology. Snowball sample techniques proved to be effective, but it has its negative consequences as well, as we do not have the complete control of the respondents.

4.5.2 Methods of analysing the collected data

To analyse the data, we used a tool called SmartPLS. We used a method called Partial Least Squares Path Modelling (PLS-SEM). This is often used when the theory is less established and when the model is complex (Hair et al., 2013, pp. 14-19). This software made it possible to visualize the conceptual model with its hypothesis and variables, as well as calculating the different measurements.

Reliability and validity
We used PLS calculations to evaluate the conceptual model. By using these calculations, it would ensure the quality of the model by helping us removing measurement errors (e.g. poorly formulated questions).

We started by completing an evaluation of the outer model. This refers to the relationships between the indicators and the connection they have to their intended measured factors (Garson, 2016, p. 60). Then we conducted an evaluation of the inner model, which refers to the paths between the latent variables (Hair et al., 2013, p. 116). Our model has both formative and reflective constructs, which are illustrated by the direction of the arrows. If the arrowhead is pointed from the first-order construct to the indicator it is reflective, and if it's the opposite, it is formative.

The main sources for checking reliability and validity in the best way has been previous master theses, the textbook by Oates (2006) and the textbook by Garson (2016). We also got a lot of help from completing the systematic literature review where we were able to look at the methods that were used in other papers. Lastly, we used several video lectures in using PLS to do these calculations as well as guidance from our supervisors.

Analysing the outer model
Our model uses multi-ordered constructs which means that this section will include measurements of the second and third order constructs as well.

Formative measurement
We started by evaluating the formative measurements. The evaluation consisted of significance and relevance of outer weights. This was done by extracting the calculated t-values and transfer them to p-values by using bootstrap on SmartPLS. Next, we did a collinearity diagnostic to see if the measurements are overlapping. This was done by looking at the Variance Inflation Factor (VIF).

Reflective measurements
The reflective measurements were evaluated by checking the reliability and discriminant validity. We started by looking at the composite reliability, Cronbach's alpha and discriminant validity. Composite reliability and Cronbach's alpha should both have values above 0.708 (Hair, Hult, Ringle & Sarstedt, 2013, p. 115). To evaluate the discriminant validity, we checked if the outer loading on the reflective indicators was higher on the construct it was measuring than on all the other constructs (Hair Jr et al., 2013, p. 105). We used the Fornell-larcker Criterion. By using the Fornell-Larcker Criterion, it made sure that the square root of the AVE was greater than any of the inter-factor correlations. Additionally, we used heterotrait-monotrait ratio (HTMT), which has been regarded as a better method for assessing the discriminant validity Henseler, Ringle and Sarstedt (2015). The threshold for HTMT is often set to be 0.90 and if the HTMT value is less than 0.90, there is discriminant validity.

Analysing the inner model
Our model consists of formative-formative and reflective-formative constructs. Therefore, we had to use a "two-step" approach (Hair Jr et al., 2013, p. 233). The usual approach for second-order constructs is "repeated indicator" if the second order construct are reflective, but in our case, the result might have corrupted values for the inner model because of the formative constructs. By completing separate assessments of the structural model (inner model) and the measurement model (outer model), it will prevent the data from being corrupted. This is because the "repeated indicator" approach would fully explain the second-order construct by the first-order construct. In our case, we had to complete the "two-step" approach in three steps, due to one of the hypotheses is regarding a second order construct within a multi-ordered construct. First, we ran a calculation on the complete model to get the latent variable score from the second and third order construct. In the second stage, we inserted these scores into the dataset used in the project. Then we created a new model with the three variables (organizational culture, big data analytic capabilities and performance) with the second order construct on BDAC (intangible resources, tangible resources and human skills) and the second order construct of organizational culture (artifacts, values, assumptions) because of our hypothesis predicts a correlation between organizational culture and intangible resources. Lastly, the third stage of the two-step approach included the development of a new model that only consisted of the three variables (organizational culture, big data analytic capabilities and performance). See figure 10 and 11 for the model illustration of the two-step reduction in stage 1 and stage 2.

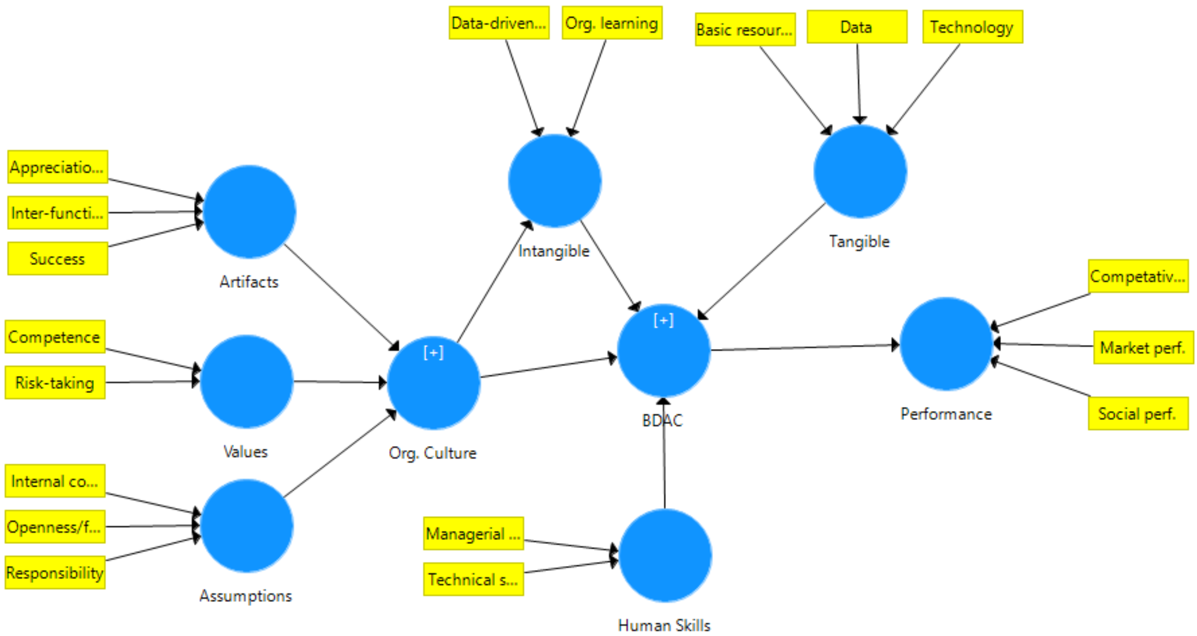

Figure 10: Two step approach, stage 1

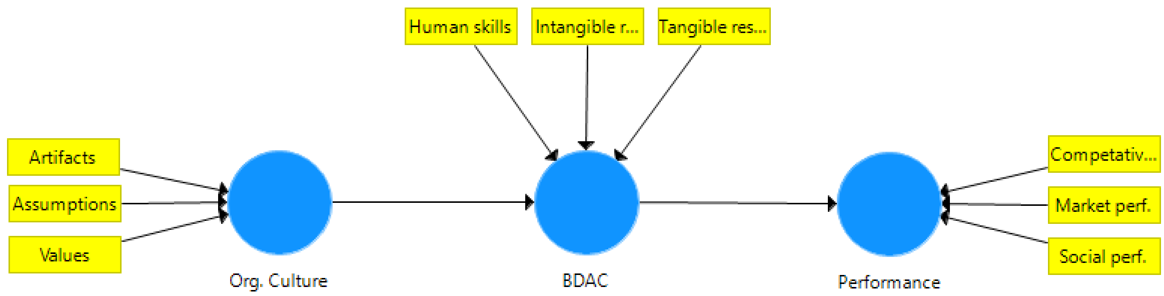

Figure 11: Two step approach, stage 2

The inner model or structural model was analysed by checking the VIF value. The value of VIF should be less than ten, because a value above ten will indicate multicollinearity (Hair, Anderson, Tatham & Black, 1995). There is however no universal agreement as what the cut-off based on values of VIF should be used to detect multicollinearity (Vatcheva, Lee, McCormick & Rahbar, 2016).

After checking all reliability and validity, the next step is to check the path coefficients and significance and their weights. When doing the significance testing, the bootstrapping procedures were based on 5000 subsamples. This is a recommendation of Hair Jr et al. (2013, p. 156).

The path coefficient interpretation was based on Kline (2005, p. 122), where he provided guidelines for new research areas. Path coefficient weights that were < 0.10 indicates a small effect, <0.30 medium effect and <50 large effect. He then mentions that if the path coefficient that is recommended is not literal, and should have a dynamic margin, where 0.49 should not be treated differently than 0.50, but as a rule of thumb, these numbers should be appropriate.

4.6 Research ethics

The study provided us with a lot of information from people working within different organizations. To get as many participants as possible without to many conflicts we decided to make the survey anonymous. This could also be seen as a weakness to the study, but we decided together with our supervisor that doing it anonymous increased the chance of getting more than 100 participants which was recommended by the literature while also making the study more credible. All the participants were informed about the nature of the research and that all the collected data would be handled anonymously. They were also free to decline to take the survey or not finishing it without any consequence.

We have done our utmost to avoid any plagiarism by carefully credit the researchers work by referencing them according to the APA 6th standard (Oates, 2006, p.61). This is also to show respect for their work.

5.0 Analysis and results

In this chapter we will present the results of our analysis. First, we present the results of the quantitative survey results which includes demographic data, reliability and validity and hypothesis testing. Then we end with a summary of this section.

5.1 Survey analysis and results

Here we will present the outcome of our analysis which was done to observe if our hypothesis would be supported or not.

5.1.1 Demographic

Our selection of participants consists of a wide range of organizations in different industries. The geographical focus was Norwegian organizations. The survey was distributed to an unknown number of organizations, due to the use of snowballing method. The snowball method also provided us with answers from different countries (e.g. Span, USA, GB, Denmark and Sweden). It was distributed through sources such as LinkedIn, where we contacted several organizations and individuals that were members of specific big data groups. We ended up with 104 respondents that fully answered the survey, and 25 that partially answered the survey, which in all cases were not usable data. Therefore, the total amount of participants was 104 and every one of them confirmed the use of big data.

Dimension	**Population (n)**
Type of company	
Private	81
Public	23
Profit	5
Non Profit	0
Company size	
0-9 employees	12
10-49 employees	21
50-249 employees	34
More than 250 employees	37
Industry	
Media	16
IT	19
Real estate	9
Service	11

Retail	4
Finance	7
Energy	9
Other	29
Country of residence	
Norway	96
Sweden	3
Denmark	2
Great Britain	1
Spain	1
USA	1

Table 12: Demographic data

5.1.2 Reliability and validity

Our study is using a deductive approach and all our variables and indicators are extracted or based from previous peer-reviewed literature. These variables and indicators were developed by the assistance of our supervisor where we ensured the quality of the variables and indicators. The development of the variables and indicators consisted of reviewing the research that has used these variables and indicators in order to make sure the testing was done accurate. Though the variables and indicators has previously been tested, it has not been tested in our model and might have a different outcome.

Evaluation of outer model
In this section, we will look at the different evaluation results described in section 4.5.2.

Formative measures
In order to measure the formative variables, we used SmartPLS to establish the validity and reliability of the outer model. We calculated the T-values of the formative indicators as a two-tailed test. Then we looked at the P-values to make sure they were below 0.05. P-values above 0.05 are also included in the table. The path coefficients (weights) were also extracted from SmartPLS. The last measurement of the formative indicators was variance inflation factor (VIF). There is no universal agreement as what the cut-off based on values of VIF should be used to detect multicollinearity (Vatcheva et al., 2016). The VIF value of formative below 10 are considered to be low multicollinearity (Hair et al., 1995). This is illustrated in table 13 and 14.

Latent variable	Indicator	Weight	T-Value	P Value	VIF
Basic resources	B1	0.629	2.844	p<0.05	2.947
	B2	0.419	**1.749**	**p<0.01**	2.947

Data	D1	0.199	**1.387**	**p<0.2**	3.071
	D2	0.404	2.082	p<0.05	3.994
	D3	0.465	2.124	p<0.05	3.432
Technology	T1	0.297	2.196	p<0.05	3.436
	T2	0.439	3.562	p<0.001	2.848
	T3	0.292	2.505	p<0.05	1.527
	T4	0.156	**1.395**	**p<0.2**	2.130

Table 13: Formative indicators value

Constructs	Measures	Weight	T-value	P-value	Vif
Artifacts	Appreciation	0.574	7.209	p<0.001	2.929
	Inter-functional co-operation	0.157	**1.558**	**p<0.1**	3.463
	Success	0.413	8.242	p<0.001	1.637
Values	Risk-taking	0.373	5.450	p<0.001	1.661
	Competence	0.722	12.451	p<0.001	1.661
Assumptions	Openness	0.235	2.656	p<0.01	2.946
	Internal communication	0.557	5.111	p<0.001	3.219
	Responsibility	0.291	2.988	p<0.01	2.595
Org. culture	Artifacts	0.478	8.546	p<0.001	6.336
	Values	0.212	4.353	p<0.001	3.788
	Assumptions	0.331	6.556	p<0.001	5.458
Intangible	Org. learning	0.357	4.975	p<0.001	1.790
	Data-driven culture	0.727	11.009	p<0.001	1.790
Tangible	Data	0.372	2.769	p<0.01	2.944
	Technology	0.427	2.983	p<0.01	3.901
	Basic resources	0.328	2.853	p<0.01	1.817
Human skills	Technical skills	0.481	8.375	p<0.001	3.686
	Managerial skills	0.557	10.160	p<0.001	3.686
BDAC	Intangible	0.363	8.925	p<0.001	3.661
	Tangible	0.281	10.523	p<0.001	2.970
	Human skills	0.429	11.167	p<0.001	3.673
Performance	Social perf.	0.489	3.054	p<0.01	1.475

Market perf.	0.223	**1.534**	**p<0.2**	2.089
Competitive perf.	0.476	3.831	p<0.01	1.892

Table 14: Formative measurement of second and third-order construct

When calculating the formative measurements, we can see that are some insignificant values between indicators and the respective first-order construct (B2, D1 and T4). We have decided to keep these indicators, due to the importance for the construct. This is acceptable because models with several formative constructs and many indicators may have some indicators that are insignificant but should be kept in the model if it is justified by the researchers (Cenfetelli and Bassellier, 2009). The same issue occurs between the first-order constructs (Inter-functional co-operation and market performance) and the second-order construct (artifacts and performance). This will also be kept in the model due to the importance for the construct.

Reflective measures

As mentioned, we were measuring Cronbach's alpha, composite reliability and indicator reliability. Cronbach's alpha and composite reliability, according to Hair et al., (2013, p. 109, 115), should have a value above 0.708 and their reflected indicator should have a loading above 0.708. We removed one indicator that were below the recommended values. This was OF1. This is illustrated in table 15 below.

Latent variable	Indicator	Loadings	Cronbach's Alpha	Composite Reliability
Appreciation of employees	AC1	0.905	0.932	0.957
	AC2	0.956		
	AC3	0.953		
Competence	CP1	0.947	0.954	0.971
	CP2	0.954		
	CP3	0.971		
Success	SU1	0.924	0.928	0.954
	SU2	0.930		
	SU3	0.949		
Risk-taking	R1	0.908	0.903	0.939
	R2	0.928		
	R3	0.910		
Openness/flexibility	OF2	0.962	0.919	0.961
	OF3	0.962		
Responsibility	RE1	0.930	0.928	0.955
	RE2	0.963		
	RE3	0.912		

Inter-functional co-operation	IF1	0.939	0.945	0.965
	IF2	0.943		
	IF3	0.966		
Internal communication	IC1	0.953	0.923	0.951
	IC2	0.934		
	IC3	0.904		
Managerial skills	MS1	0.900	0.954	0.963
	MS2	0.893		
	MS3	0.909		
	MS4	0.853		
	MS5	0.915		
	MS6	0.944		
Technical skills	TS1	0.904	0.955	0.968
	TS2	0.943		
	TS3	0.957		
	TS4	0.952		
Org. learning	OL1	0.938	0.959	0.968
	OL2	0.920		
	OL3	0.923		
	OL4	0.943		
	OL5	0.908		
Data-driven culture	DD1	0.874	0.939	0.953
	DD2	0.878		
	DD3	0.891		
	DD4	0.923		
	DD5	0.914		
Competitive perf.	COP1	0.771	0.903	0.925
	COP2	0.747		
	COP3	0.839		
	COP4	0.883		
	COP5	0.824		
	COP6	0.852		
Market perf.	MP1	0.789	0.843	0.894
	MP2	0.824		

	MP3	0.870		
	MP4	0.812		
Social perf.	SP1	0.770	0.859	0.905
	SP2	0.849		
	SP3	0.895		
	SP4	0.838		

Table 15: Formative measurement of second and third-order construct

The discriminant validity was assessed by creating an overview over the cross loadings and checked that the indicators measured what they were supposed to. See table 16 below.

Items	Appreciation of e	Competative per	Competence	Data-driven cultu	Internal commun	Inter-functional c	Market perf.	Mangerial skills	Openness/flexibi	Org. learning	Risk-taking	Responsibility	Social perf.	Success	Technical skills
ac1	**0.905**	0.425	0.683	0.661	0.739	0.745	0.476	0.611	0.763	0.493	0.500	0.714	0.627	0.598	0.563
ac2	**0.955**	0.520	0.643	0.656	0.770	0.791	0.482	0.567	0.790	0.422	0.512	0.600	0.654	0.444	0.480
ac3	**0.954**	0.546	0.637	0.690	0.774	0.750	0.510	0.578	0.766	0.529	0.478	0.588	0.663	0.431	0.532
cop1	0.459	**0.773**	0.497	0.638	0.527	0.485	0.603	0.486	0.435	0.547	0.545	0.410	0.339	0.539	0.325
cop2	0.244	**0.747**	0.337	0.368	0.262	0.172	0.469	0.232	0.146	0.375	0.232	0.178	0.148	0.332	0.161
cop3	0.476	**0.841**	0.505	0.549	0.503	0.410	0.570	0.433	0.384	0.481	0.447	0.365	0.331	0.489	0.346
cop4	0.501	**0.883**	0.569	0.491	0.565	0.523	0.589	0.458	0.406	0.485	0.441	0.564	0.555	0.537	0.459
cop5	0.469	**0.822**	0.476	0.404	0.472	0.483	0.523	0.524	0.465	0.379	0.462	0.559	0.475	0.528	0.535
cop6	0.421	**0.850**	0.486	0.371	0.439	0.412	0.560	0.441	0.359	0.429	0.376	0.522	0.439	0.507	0.445
cp1	0.657	0.544	**0.947**	0.547	0.741	0.752	0.605	0.515	0.633	0.535	0.556	0.780	0.564	0.714	0.491
cp2	0.648	0.580	**0.954**	0.583	0.696	0.670	0.689	0.586	0.662	0.559	0.641	0.729	0.577	0.758	0.539
cp3	0.699	0.566	**0.972**	0.609	0.729	0.763	0.653	0.531	0.684	0.558	0.618	0.720	0.539	0.723	0.522
dd1	0.658	0.453	0.577	**0.874**	0.685	0.623	0.465	0.667	0.631	0.626	0.534	0.513	0.564	0.562	0.612
dd2	0.625	0.443	0.529	**0.876**	0.641	0.555	0.452	0.616	0.502	0.605	0.398	0.464	0.528	0.478	0.536
dd3	0.594	0.528	0.485	**0.892**	0.528	0.530	0.535	0.613	0.512	0.539	0.474	0.459	0.483	0.579	0.447
dd4	0.686	0.567	0.559	**0.924**	0.632	0.568	0.564	0.708	0.570	0.615	0.546	0.468	0.496	0.558	0.634
dd5	0.633	0.571	0.563	**0.915**	0.598	0.581	0.551	0.676	0.513	0.591	0.548	0.461	0.552	0.585	0.608
ic1	0.751	0.560	0.744	0.619	**0.951**	0.753	0.537	0.522	0.790	0.587	0.562	0.782	0.646	0.588	0.528
ic2	0.802	0.534	0.727	0.685	**0.936**	0.793	0.497	0.515	0.676	0.584	0.488	0.689	0.669	0.559	0.504
ic3	0.712	0.498	0.630	0.619	**0.905**	0.778	0.417	0.501	0.728	0.519	0.552	0.625	0.621	0.535	0.564
if1	0.737	0.420	0.725	0.522	0.730	**0.936**	0.481	0.519	0.714	0.440	0.535	0.733	0.611	0.571	0.475
if2	0.814	0.537	0.731	0.692	0.847	**0.946**	0.544	0.491	0.774	0.530	0.613	0.686	0.678	0.581	0.471
if3	0.757	0.504	0.710	0.592	0.785	**0.965**	0.492	0.490	0.709	0.389	0.609	0.709	0.684	0.620	0.448
mp1	0.482	0.462	0.539	0.536	0.437	0.367	**0.800**	0.484	0.419	0.473	0.429	0.485	0.476	0.512	0.477
mp2	0.522	0.582	0.591	0.499	0.534	0.536	**0.836**	0.474	0.381	0.639	0.341	0.573	0.598	0.422	0.466
mp3	0.406	0.567	0.622	0.457	0.405	0.471	**0.861**	0.466	0.420	0.443	0.476	0.463	0.355	0.573	0.406
mp4	0.303	0.606	0.482	0.400	0.330	0.374	**0.798**	0.402	0.328	0.307	0.437	0.412	0.367	0.583	0.305
ms1	0.525	0.426	0.474	0.597	0.480	0.476	0.459	**0.898**	0.543	0.562	0.521	0.549	0.528	0.470	0.807
ms2	0.554	0.465	0.529	0.642	0.518	0.467	0.534	**0.894**	0.528	0.660	0.519	0.536	0.504	0.485	0.740
ms3	0.583	0.466	0.557	0.612	0.490	0.519	0.509	**0.908**	0.574	0.581	0.555	0.612	0.488	0.480	0.776
ms4	0.636	0.556	0.512	0.799	0.608	0.551	0.522	**0.857**	0.578	0.605	0.582	0.548	0.545	0.489	0.720
ms5	0.534	0.449	0.499	0.632	0.410	0.392	0.484	**0.914**	0.508	0.578	0.475	0.509	0.412	0.464	0.711
ms6	0.546	0.502	0.507	0.680	0.470	0.440	0.488	**0.943**	0.526	0.607	0.517	0.567	0.491	0.498	0.805
of2	0.793	0.448	0.684	0.589	0.751	0.728	0.497	0.586	**0.962**	0.476	0.607	0.702	0.623	0.517	0.559
of3	0.792	0.425	0.642	0.582	0.760	0.759	0.404	0.572	**0.961**	0.425	0.566	0.695	0.585	0.531	0.522
ol1	0.484	0.526	0.573	0.628	0.616	0.505	0.538	0.593	0.493	**0.937**	0.427	0.501	0.419	0.422	0.585
ol2	0.445	0.460	0.530	0.575	0.553	0.421	0.476	0.537	0.398	**0.918**	0.283	0.440	0.312	0.371	0.504
ol3	0.536	0.533	0.547	0.680	0.578	0.437	0.538	0.648	0.433	**0.924**	0.396	0.513	0.429	0.462	0.597
ol4	0.461	0.508	0.527	0.622	0.500	0.429	0.583	0.666	0.426	**0.943**	0.370	0.482	0.415	0.398	0.639
ol5	0.449	0.509	0.487	0.564	0.561	0.426	0.500	0.624	0.418	**0.909**	0.357	0.524	0.420	0.428	0.615
r1	0.562	0.545	0.620	0.593	0.628	0.626	0.488	0.514	0.583	0.459	**0.913**	0.580	0.503	0.605	0.475
r2	0.527	0.459	0.587	0.500	0.523	0.583	0.455	0.604	0.600	0.386	**0.928**	0.586	0.451	0.550	0.498
r3	0.344	0.393	0.521	0.428	0.404	0.476	0.448	0.486	0.481	0.225	**0.905**	0.480	0.425	0.543	0.427
re1	0.661	0.441	0.654	0.510	0.703	0.720	0.488	0.584	0.701	0.479	0.520	**0.930**	0.632	0.666	0.548
re2	0.671	0.546	0.717	0.489	0.723	0.708	0.563	0.594	0.718	0.483	0.576	**0.963**	0.659	0.640	0.521
re3	0.565	0.533	0.808	0.481	0.685	0.667	0.603	0.544	0.616	0.531	0.598	**0.913**	0.604	0.712	0.542
sp1	0.535	0.347	0.581	0.386	0.559	0.589	0.530	0.464	0.611	0.379	0.501	0.667	**0.765**	0.588	0.419
sp2	0.579	0.401	0.421	0.507	0.559	0.556	0.409	0.395	0.462	0.274	0.370	0.520	**0.853**	0.377	0.379
sp3	0.617	0.403	0.561	0.588	0.645	0.687	0.532	0.496	0.522	0.456	0.432	0.589	**0.895**	0.477	0.548
sp4	0.586	0.453	0.398	0.473	0.562	0.491	0.369	0.485	0.518	0.336	0.395	0.495	**0.839**	0.345	0.559
su1	0.466	0.505	0.718	0.514	0.559	0.556	0.585	0.511	0.546	0.405	0.614	0.708	0.525	**0.924**	0.461
su2	0.404	0.536	0.630	0.539	0.450	0.479	0.517	0.429	0.408	0.325	0.505	0.567	0.410	**0.931**	0.346
su3	0.583	0.632	0.782	0.662	0.662	0.689	0.653	0.545	0.560	0.514	0.612	0.725	0.544	**0.949**	0.483
ts2	0.521	0.451	0.437	0.572	0.484	0.427	0.418	0.732	0.497	0.587	0.463	0.447	0.518	0.391	**0.904**
ts3	0.514	0.439	0.530	0.560	0.556	0.472	0.446	0.783	0.516	0.594	0.467	0.570	0.540	0.453	**0.943**
ts4	0.526	0.447	0.517	0.622	0.538	0.441	0.522	0.827	0.551	0.602	0.490	0.557	0.522	0.452	**0.957**
ts5	0.544	0.439	0.543	0.628	0.564	0.498	0.496	0.820	0.545	0.607	0.502	0.576	0.561	0.445	**0.952**

Table 16: Cross loadings

The Fornell-Larcker criterion was extracted and calculated by smartPLS. See table 17 below.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Appreciation of	**0.938**														
Competative pe	0.529	**0.821**													
Competence	0.698	0.589	**0.957**												
Data-driven cul	0.714	0.573	0.606	**0.896**											
Inter-functional	0.812	0.515	0.761	0.638	**0.949**										
Internal commu	0.812	0.571	0.753	0.688	0.832	**0.931**									
Mangerial skills	0.625	0.530	0.568	0.733	0.526	0.551	**0.903**								
Market perf.	0.522	0.674	0.679	0.574	0.534	0.521	0.554	**0.824**							
Openness/flexil	0.824	0.454	0.689	0.609	0.773	0.786	0.602	0.468	**0.962**						
Org. learning	0.514	0.548	0.576	0.664	0.480	0.606	0.664	0.570	0.469	**0.926**					
Responsibility	0.677	0.541	0.775	0.528	0.747	0.752	0.614	0.589	0.726	0.532	**0.935**				
Risk-taking	0.530	0.514	0.633	0.560	0.619	0.574	0.586	0.508	0.610	0.398	0.603	**0.915**			
Social perf.	0.691	0.478	0.585	0.585	0.694	0.694	0.549	0.549	0.629	0.432	0.676	0.505	**0.839**		
Success	0.525	0.601	0.764	0.617	0.622	0.603	0.533	0.631	0.545	0.450	0.718	0.620	0.532	**0.935**	
Technical skills	0.560	0.472	0.540	0.635	0.490	0.571	0.843	0.502	0.562	0.636	0.574	0.512	0.570	0.464	**0.939**

Table 17: Fornell-Larcker criterion

Then we checked the Heterotrait-monotrait ratio (HTMT) and looked at their values. The threshold for establishing if there are discriminant validity is 0.90 (Gold & Arvind Malhotra, 2001; Teo, Srivastava & Jiang, 2008). As illustrated in table 18 below, all our values are below 0.90, which establishes discriminant validity.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Appreciation of employees															
Competative perf.	0.570														
Competence	0.740	0.628													
Data-driven culture	0.762	0.622	0.639												
Inter-functional co-operation	0.864	0.544	0.801	0.673											
Internal communication	0.875	0.616	0.802	0.740	0.889										
Mangerial skills	0.662	0.563	0.595	0.773	0.554	0.586									
Market perf.	0.586	0.770	0.755	0.645	0.593	0.586	0.617								
Openness/flexibility	0.891	0.490	0.736	0.656	0.828	0.854	0.643	0.533							
Org. learning	0.542	0.588	0.601	0.699	0.501	0.644	0.692	0.627	0.499						
Responsibility	0.726	0.577	0.826	0.566	0.798	0.811	0.652	0.664	0.786	0.564					
Risk-taking	0.569	0.558	0.677	0.600	0.662	0.620	0.629	0.584	0.665	0.416	0.655				
Social perf.	0.773	0.528	0.646	0.650	0.768	0.779	0.606	0.640	0.710	0.473	0.758	0.572			
Success	0.556	0.647	0.807	0.655	0.656	0.644	0.563	0.712	0.585	0.469	0.770	0.672	0.593		
Technical skills	0.593	0.497	0.565	0.668	0.515	0.609	0.881	0.558	0.599	0.664	0.608	0.549	0.627	0.488	

Table 18: Heterotrait-monotrait ratio (HTMT)

Evaluation of inner model

By looking at the VIF (variance inflation factor), we determined the reliability and validity of the inner model (structural model). Next, we checked the path coefficient and its respective t-values and p-values of the relevant paths of the inner model. The relevant paths refer to the constructs that are used in the hypotheses. This is illustrated in table 19 below.

Paths	Weight	T value	P value	VIF
Org. Culture -> Intangible	0.805	18.677	p<0.001	1.000
BDAC -> Performance	0.757	12.284	p<0.001	1.000
Org. Culture -> BDAC	0.769	15.900	p<0.001	1.000

Table 19: Relevant path of Inner model values

5.1.3 Hypotheses testing

Now that the reliability and validity of the complete research model is in order, we evaluated the hypotheses. We have three hypotheses in our model. The path coefficient weights should be above 0.50 according to Hair, Ringle & Sarstedt, (2011). If the weight is around 0.10, it indicates a small effect, 0.30 indicates medium effect. In the following section, we will look at different hypotheses and their weighting in order to see if it is supported or falsified.

Hypothesis 1: "Organizational culture has a positive effect on big data analytic capabilities"
Hypothesis 1 had a weight of 0.769, which is heavily supported with a t-value of 15.900 which equals a p-value of less than 0.001. The reliability and validity were acceptable, which confirms that the hypothesis is supported.

Hypothesis 2: "Big data analytic capability has a positive effect on firm performance"
Hypothesis 2 had a weight of 0.757 and a t-value of 12.284 which equals a p-value of less than 0.001. The reliability and validity were acceptable which confirms that the hypothesis is supported.

Hypothesis 3: "Organizational culture has a positive effect on Intangible resources"
Hypothesis 3 had a weight of 0.805 and a t-value of 18.677 which equals a p-value of less than 0.001. The reliability and validity were acceptable which confirms that the hypothesis is supported.

Hypothesis	Independent variable	Dependent variable	Weight	T-value	P-value	Conclusion
H1	Org. culture	BDAC	0.769	15.900	$p<0.001$	Supported
H2	BDAC	Performance	0.757	12.284	$p<0.001$	Supported
H3	Org. culture	Intangible	0.805	18.677	$p<0.001$	Supported

Table 20: Hypotheses conclusions

6.0 Discussion

In this chapter, we discuss our findings.

Our study is based on previous research were the measurement of big data analytic capabilities and the connection between big data analytic capabilities and firm performance has been confirmed. The connection between organizational culture and big data analytic capabilities or intangible resources have not been tested empirically in the past. This is based on the systematic literature review, showing that based on our knowledge and gathered information, there has not been similar studies done. This is especially true when looking at studies who have Norwegian organizations as their primary demographic.

We begin by summarizing the findings of our research study. First, we discussed our research question and our three hypotheses. Second, we discussed other findings. Third, we discussed the reliability and validity of the results we acquired from the associated test. Fourth, we discuss the implications of the research both theoretically and practically. Finally, we conclude the chapter by discussing limitations and suggestions for future work.

6.1 Summary of research

The main goal of this research is to explain how organizations can develop big data analytic capabilities by changing their organizational culture. This is measured through firm performance. Even though the phrase big data is often looked at as a buzzword og catchphrase, it is getting a lot of attention the past years where a lot of research within this field has been conducted. The previous research has often regarded the technical aspect of big data and looking at different technical challenges and barriers that might occur when investing in big data. We wanted to look deeper into the effect that organizational culture has on big data, based on previous literature that always points at the importance of non-technical skills that is needed for successfully adopting big data (Shamim et al., 2018; Adrian et al., 2016).

By conducting a systematic literature review, we managed to identify research gaps that were often discussed briefly in many of the previous articles. The main issue we identified is the organizational culture and the cultural impact on adopting big data and become data-driven. By changing the perspective of looking through a technical lens when researching big data, we had to change our view towards an organizational point of view.

In order for us to test the hypotheses we developed, we used a quantitative approach, where we gathered a sample of 104 organizations, where most of them were from Norway. The analysis was performed by using Partial Least Squares Structural Equation Modeling (PLS-SEM), where it was done by a software called SmartPLS.

6.2 Discussion of the RQ and hypotheses

The research question was:” **To what extent does organizational culture affect an organization's ability to adopt and use big data?**”. To answer the research question, we looked at organizational culture’s effect on big data analytic capabilities, where two of hypotheses was developed (H1 and H3). Both of these hypotheses were significant and had a high path coefficient values and it is established that organizational culture has a positive effect on big data analytics capabilities. The last hypothesis was developed in order to measure the impact of organizational culture on big data analytics through firm performance (H2), where we looked at the impact of big data analytic capabilities and firm performance. This hypothesis was also confirmed by having a high path coefficient and being significant.

We have interpreted the findings based on the path coefficients that links the hypothesis latent variables and looking at their significance to rule out the possibility of chance and other unknown factors have an impact. This is presented in the next section.

Hypothesis 1: “Organizational culture has a positive effect on big data analytic capabilities”

Hypothesis 1 was strongly supported with a significant of $p<0.001$ and the path coefficient weight was 0.769 which is a very high effect. This positive effect was our prediction, where several published papers has suggested a strong effect between organizational culture and big data analytic capabilities. Due to the rapid development in technology, where everything happens instantaneous, fast moving and large amount of data is important in order for organizations to keep up with the environment. Organizations often tries to invest in big data analytics, but often seem to fail due to their capabilities. These findings can help organizations aim towards the important factors when implementing big data analytics and look at the organizational factors, instead of the technical factors and the expertise and increase their performance.

Hypothesis 2: “Big data analytic capability has a positive effect on firm performance”

Hypothesis 2 has previously been tested and are also confirmed in our study with a high path coefficient weight of 0.757 and a p-value of less than 0.001. By looking through big data analytic capabilities through a resource based view, it will positively affect the performance of an organization. Most of the literature already agrees that big data analytic capability will increase an organization's performance.

Hypothesis 3: “Organizational culture has a positive effect on Intangible resources”

Hypothesis 3 is a more unconventional hypothesis, where we look at the direct effect of organizational culture on one specific dimension of big data analytic capabilities. We decided to look at this path, since previous literature often points at importance of intangible resources when adopting big data analytic capabilities. Literature often points at intangible resources (organizational learning and data-driven culture) as resources that organizations can change for employees to exploit and expand their knowledge and adequately integrate the knowledge to make better decisions. Intangible resources defined by Gupta & George (2016) are resources that are highly connected to organizational culture. Making changes to the data-driven culture and organizational learning often includes changing the values and norms employees have around big data and may therefore captivate the necessary resources to understand the value big data can have on their firms' performance.

6.3 Discussion of the reliability and validity

The measurement of reliability and validity in this study was conducted by various sources. We attempted to look at textbooks that were recommended by the institute from previous courses, as well as previous written master thesis. Besides textbooks and master theses, we got a lot of help from our supervisors. We only had a basic understanding of how to measure validity and reliability but had to make sure these two measurements were established in order to have a contribution to the field. In regard to validity and reliability, most of our values are acceptable according to the thresholds, but there were some that should have been looked closer to.

In the outer model, there were three formative indicators that had a negative t-value which also includes a high p-value. We decided to keep them all, based on its importance to the respective variable. By keeping the indicators, we got a whole measure of the variables. The same issue occurred in the second and third order constructs, where inter-functional co-operation had a low t-value but were kept in order to get measures of all the suggested dimensions of the variable. The last instance where we had a low t-value were at market performance. This was also included in the study in order to get measures of different dimensions of firm performance.

As stated in 5.1.2, Cenfetelli and Bassellier (2009) suggest that in a model with very many indicators there is a huge probability that some of them will be insignificant, but should be kept in order to get a complete measure of the variable if it is justified by the researchers. This is the reason why we decided to keep all the indicators that had a value below the recommended threshold. Regarding the reflective indicators, all indicators were on the good side of the thresholds and were included in the study. Overall, all our hypotheses had reliability and validity and were supported.

6.4 Discussion of other findings

Or research provided us with a good amount of data and information that can be a source for further analysis.

We found that inter-functional cooperation did not have any significant effect on the Artifact construct. The effect had a high p-value and a low t-value which means it is insignificant.

We heard from some of the respondents that the questions associated with the BDAC construct, especially the technology part, was hard to understand. This may be due to the fact that the respondents did not actively use big data in their work, but work in an organization that uses it. This means that not all of them will be as technically sound and informed about big data. Gathering data from them is important, because it will provide us with a better representation of the organizational culture in the organization.

6.5 Discussion of the research process

In this section, we discuss our thoughts regarding the research process conducted in this project.

Literature review
We chose to focus on organizational culture within the big data field. The reason being that organizational culture was mentioned in most of the articles regarding big data analytic capabilities as an important factor of developing big data analytic capabilities and it was a clear research gap within this field.

Data collecting process
This process can be the most time-intensive job for the researchers. We tried to combine this phase with writing and doing other tasks while waiting for answers. After some time and lack of responses we agreed to devote all our time to get as many respondents as possible. We knew that writing a standardized bulk email would decrease the chance of people responding. So, each email we wrote was written with the respondent's name on top, so that they knew their email was unique. We did this to all the people we sent an email to. We also provided them with information about us and the study we conducted. This was done by just writing a few sentences that was easy to read, and for them to get a grasp of the study. Giving them information about the study and our self, also built trust. The data collecting process was anonymous, so we did not have the luxury of knowing the people who did not respond or finish the survey. Getting people to respond and complete the survey via email turned out to be really hard. We then had to start calling people, which was by far the best way of getting them to complete the survey. Other methods we used were getting into big data groups on LinkedIn and contacting people on LinkedIn.

Some of the respondents answered that they did not use big data but completed or almost completed the survey. Not sure why this happened, but we should have made the survey end if they chose it since their contribution would not be of any value.

We should also have done some form of trial survey on members that work in organizations that uses big data. This to provide some feedback about the questions, length of the survey and more information that we could use to refine it before sending it out.

The planning of the analysis process
We would have given ourselves more time to do the analysis, due to many of the unforeseen challenges that arose. Many of them being with getting to know the software SmartPLS and how to analyse second and third order constructs correctly.

6.6 Implications

This study has some interesting findings that can be used in further research and applied to organizations for practical use.

Our results on big data analytic capabilities showed similar results as Gupta & George (2016) except for a few insignificant effects. Our research therefore supports their third-order construct for big data analytic capabilities. When looking at the results we got from their formative measurements coupled with previous studies showing the same effect, it would be interesting to change questions or use reflective measurements instead. Their formative questions have good scientific backing and should provide good measurements, but in our analysis and others it has shown that some of them are insignificant.

Our research provides a good base for trying to understand concepts like big data analytic capabilities and organizational culture. Researchers with a deeper understanding and expertise on these concepts can therefor improve these by refining our model and or measures.

Organizational culture having such a positive effect on big data analytic capabilities, provide a research area for development of components that will strengthen this connection. It also shows that organizations that are not as technically sound or knowledgeable about big data, could and should focus on their organizational culture. This shows that focusing on the organizational culture will increase the chance of having success with big data initiatives. The reason for this may be due to developing a culture within the organization that understands, are open to, values and wants to learn about the possible benefits big data can bring to the organization.

The research phases we developed will hopefully provide readers with useful tips when conducting a similar data collecting phase.

6.7 Limitations and future work

There were some limitations to our research. Our constructs were based on previous research, but our research model with everything connected is complicated. The firm performance and organizational culture constructs can be refined and improved even further to get more significant values, like improvement on the inter-functional cooperation which showed to be nonsignificant.

When collecting our data, we used many methods. One of them was going on big data groups on LinkedIn. This gives us less control of who is taking our survey, because it can be people that are just interested in big data that are a member of the group but are not working in organizations that uses it. The people that came from this LinkedIn groups however did not make up much or any of the participants in our survey. We also used the snowball effect; were we encourage people to send the survey to people they know that work in organizations that uses big data. This method also gives us less control and make the data collected from this method less reliable. Once again, we did not get much or any data from this method.

The survey had some technical questions that may be hard to understand for certain participants, since we wanted a broad range of people within organizations to take the survey. This to get a better representation of the whole organizational culture, since CEO`s, people working with big data and regular employees all have different views on their organization. Also, the interpretation of the 1-7 scale can differ. Rating the question seven means they totally agree, but some participants may feel seven is perfect and pick six, even though they are in the same agreement as another one that picked seven. This may just come down to people preferring extreme values while others prefer to position themselves in the middle.

Having a bigger sample size of data could provide us with the ability to look at differences in regard to the respective industries or the size of the organizations.

Our survey contained many questions that we did not use in our model and made the survey quite big. The amount of questions may be the reason many of the participants did not complete the survey. The whole survey is shown in the Appendix.

Improvement of the big data analytic capabilities construct in regard to its formative measurements that may lead to better measures if switched to reflective. Also looking to improve the questions by changing them or making them easier to understand for people that not work extensively with big data.

There are several gaps in the research regarding organizational culture and big data analytics. First, it would be interesting to see a study integrating moderating factors such as environmental factors or other capabilities that is proven to have an effect on BDAC. Additionally, a refinement of the formative indicators on the second-order construct of BDAC (tangible resources), due to the insignificance.

7.0 Conclusion

This study aimed to highlight the importance of organizational culture on big data analytic capabilities and organizations ability to successfully adopt big data. In order to highlight this challenge, we answered the following research question: “To what extent does organizational culture affect an organization's ability to adopt and use big data?”

The research question was answered by developing a survey and distributing it to 104 different respondents that actively used big data in their organization. We analysed the data by using partial least squares structural equation modelling (PLS-SEM) with the tool, SmartPLS.

We started by doing a systematic literature review to increase our knowledge about the topic. Then we developed a conceptual model and the survey. The next step was data collection, where we distributed the survey to an unknown number of big data users in order to get an acceptable number of respondents. Lastly, we analysed the data and tested the hypotheses.

Our analysis showed significant support for all three hypotheses, where they all had a strong path coefficient weight. This means that organizations that focuses on organizational culture, will have an easier time developing big data analytic capabilities and be capable of fully utilizing big data analytics. Practically, this means that organizations with better organizational culture will be able to use analytics in their day-to-day operations and gain better insight into the continuously changing environment.

To answer our research question, there are clearly a huge impact of organizational culture on organizations big data adoption. This also indicates that organizations that are planning to invest in big data solutions, might want to redirect their focus to organizational culture first instead of the technology itself in order to successfully utilize this new technology.

8.0 References

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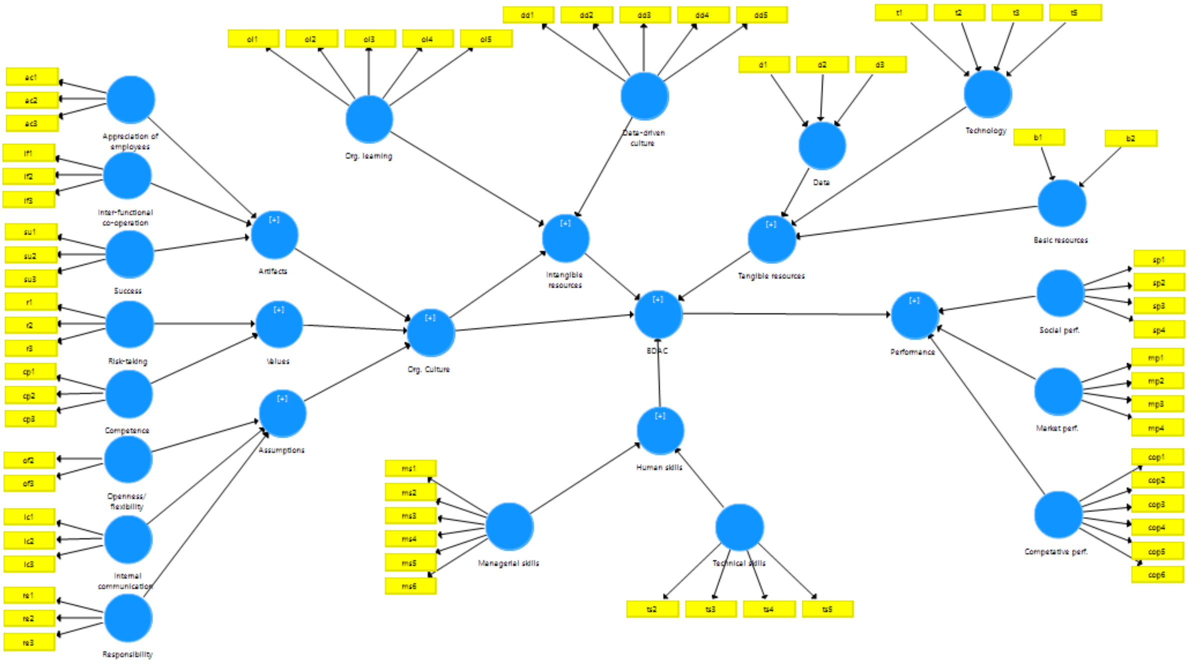
9.0 Appendix

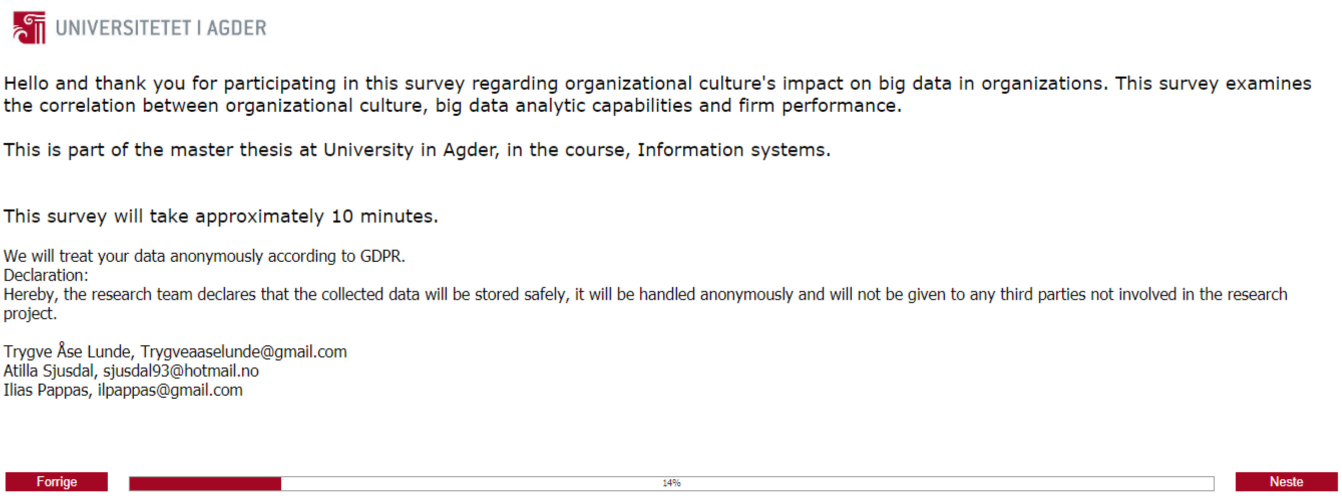
Appendix 1: Complete model

Figure 12: Complete model



Appendix 2: Survey

Figure 13: Original survey



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Hello and thank you for participating in this survey regarding organizational culture's impact on big data in organizations. This survey examines the correlation between organizational culture, big data analytic capabilities and firm performance.

This is part of the master thesis at University in Agder, in the course, Information systems.

This survey will take approximately 10 minutes.

We will treat your data anonymously according to GDPR.
Declaration:
Hereby, the research team declares that the collected data will be stored safely, it will be handled anonymously and will not be given to any third parties not involved in the research project.

Trygve Åse Lunde, Trygveaaselunde@gmail.com
Atilla Sjusdal, sjusdal93@hotmail.no
Ilias Pappas, ilpappas@gmail.com

Forrige 14% Neste

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Do you use big data in your organization?
- Yes
- No
- I don't know

Type of company
- Private
- Public
- Profit
- Non profit

Company size (amount of employees)
- 0-9 employees
- 10-49 employees
- 50-249 employees
- More than 250 employees

Country of residence

What type industry do you work in?

Organizational culture

Openness/willingness
Answer the questions by reflecting on your own experience in your organization.

1 - Totally disagree, 7 - Totally agree

	1	2	3	4	5	6	7
We value openness and responsiveness in this firm							
We place great value on being flexible in our approach to problems							
A Willingness to show flexibility and openness is valued within this firm							

Internal communication

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
Open communication is valued highly within this firm							
We place great value on excellent internal communication within this firm							
Maintaining high quality internal communication is valued within this firm							

Inter-functional co-operation

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
Cooperation among different work teams is valued highly							
This firm values integration and sharing among teams throughout the firm							
We place great value on co-coordination among different work teams							

Risk taking

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
The firm values a willingness to challenge the status quo							
This firm values a willingness to experiment with new ideas							
Valuing calculated risk-taking helped this firm get to where it is today							

Competence and professionalism

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
We place great value on professional knowledge and skills							
We aspire to a high level of competence and professionalism							
Upholding the highest levels of professionalism is valued within this firm							

Appreciation of employees

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
We place great value on recognizing and rewarding employees' accomplishments							
Taking time to celebrate employee's work achievements is valued in this firm							
We place great value on showing our appreciation for the efforts of each employee							

Responsibility

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
We place great value on every employee being proactive in his/her role							
The firm values employees using their initiative							
We value employees taking responsibility for their work							

Success

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
We value success in this firm							
We aspire to be the best firm in our market							
We place great value on our performance							

Social performance

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
Our firm believes in gender equality							
Our firm pays significant attention to the mortality rate of the daily wage workers children							
Our firm believes in poverty reduction							
Our firm pays significant attention to the nutritional status of the meal served in the canteen							

Market performance

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
Our firm is achieving client satisfaction							
Our firm is able to keep the current clients							
Our firm is attracting new clients							
Our firm is attaining desired growth							

Competitive advantage

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
We have gained strategic advantages over our competitors							
We have a large market share							
Overall, we are more successful than our major competitors							
Our EBIT (earnings before interest and taxes) is continuously above industry average							
Our ROI (return on investment) is continuously above industry average							
Our ROS (return on sales) is continuously above industry average							

Data

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
We have access to very large, unstructured, or fast-moving data for analysis							
We integrate data from multiple internal sources into a data warehouse or mart for easy access							
We integrate external data with internal to facilitate high-value analysis of our business environment							

Technology

We have explored or adopted:

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
parallel computing approaches (e.g. Hadoop) to big data processing							
different data visualization tools							
cloud-based services for processing data and performing analytics							
new forms of databases such as NotOnlySQL (NoSQL) for storing data							

Technical skills

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
We hire new employees that already have the big data analytics skills							
Our big data analytics staff has the right skills to accomplish their jobs successfully							
Our big data analytics staff has suitable education to fulfill their jobs							
Our big data analytics staff holds suitable work experience to accomplish their jobs successfully							

Managerial skills

Our big data analytics managers:

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
understand and appreciate the business needs of other functional managers, suppliers, and customers							
are able to work with functional managers, supplier and customers to determine opportunities that big data might bring to our business							
are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers							
are able to anticipate the future business needs of functional managers, suppliers, and customers							
have a good sense of where to apply big data							
are able to understand and evaluate the output extracted from big data							

Basic resources

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
Our big data analytics projects are adequately funded							
Our big data analytics projects are given enough time to achieve their objectives							

Data-driven culture

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
We considered data a tangible asset							
We base our decisions on data rather than on instinct							
We are willing to override our own intuition when data contradict our viewpoints							
We continually assess and improve the business rules in response to insights extracted from data							
We continuously coach our employees to make decisions based on data							

Intensity of Organizational learning

	1-Totally disagree, 7-Totally agree						
	1	2	3	4	5	6	7
We are able to search for new and relevant knowledge							
We are able to acquire new and relevant knowledge							
We are able to assimilate relevant knowledge							
We are able to apply relevant knowledge							
We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge							

Thanks for participating in the survey!

For questions regarding the research, please contact:
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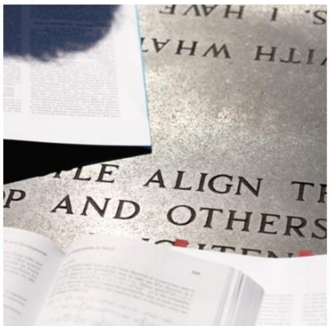

These were not used in our thesis

Figure 14: Items not used in the thesis

Process procedural practices

In our organization, we have controlled practices regarding data management in terms of _______

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
Setting retention policies (e.g. user access) to data	○	○	○	○	○	○	○
Backup routines	○	○	○	○	○	○	○
Establishing/monitoring access (e.g. user access) to data	○	○	○	○	○	○	○
Classifying data according to value	○	○	○	○	○	○	○
Monitoring costs versus value of data	○	○	○	○	○	○	○

Dynamic capabilities

Please indicate the degree to which the use of big data analytics tools in the last three years has helped to:

1-Totally disagree, 7-Totally agree

	1	2	3	4	5	6	7
Develop new product or service	○	○	○	○	○	○	○
Implement new business process	○	○	○	○	○	○	○
Create new customers relationships	○	○	○	○	○	○	○
Change way of doing business	○	○	○	○	○	○	○