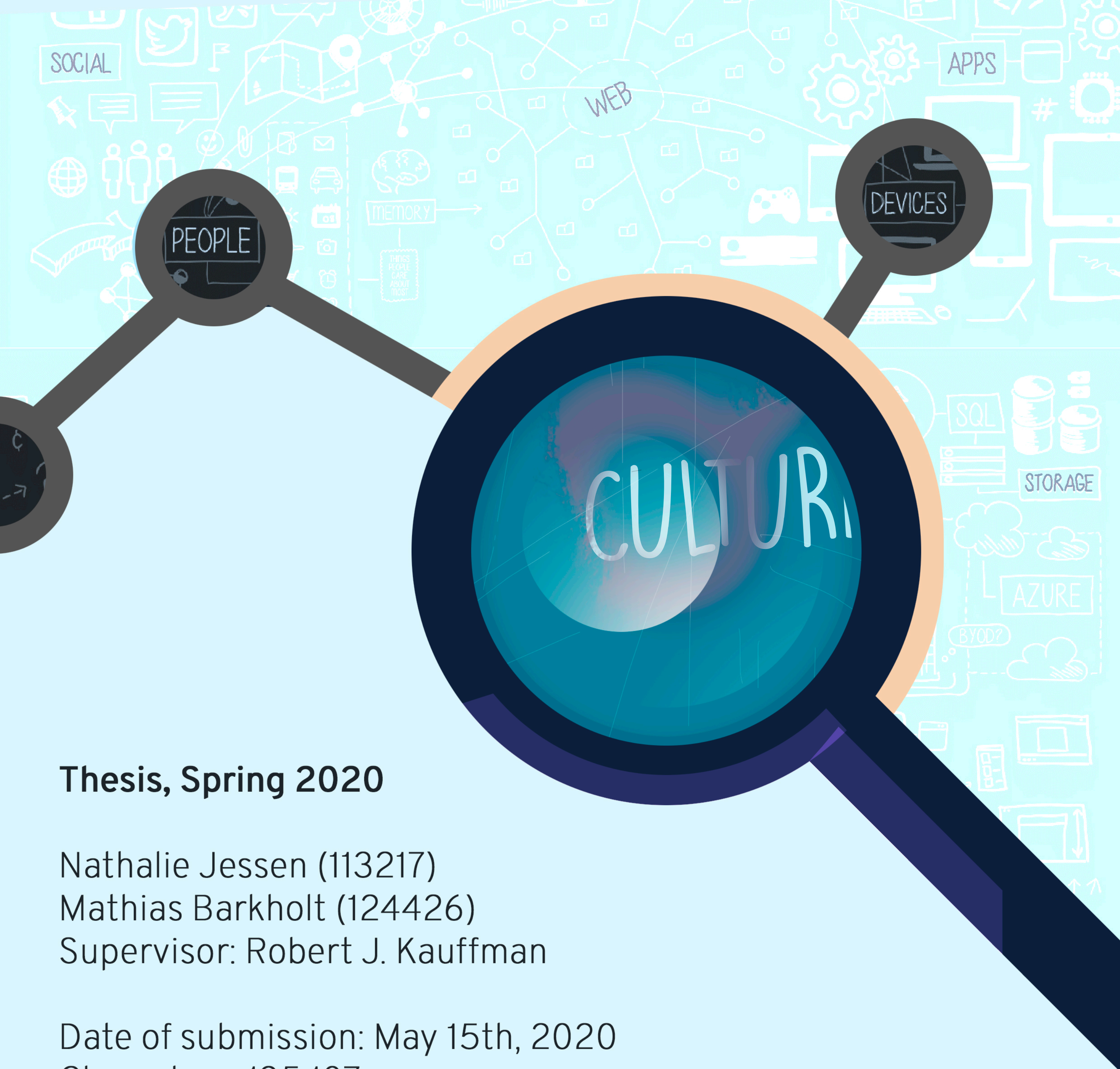
Data Culture in Organizations:

A framework for culture transition



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Abstract

With the ongoing data revolution, entire business processes are being revised and organizations all over the world are facing similar challenges in a changing competitive landscape. The quest of becoming data driven has become a matter of survival. However, surprisingly few companies have made the transition to the extent where data analytics becomes the powerful tool it has the potential to be. And our overall findings indicate that it is overlooked in academia as well. This study maps the disconnection in organizations and ascribe the gap to the lack of an underlying organizational culture, which supports and promotes data driven behavior and a data agenda. We find three general characteristics in our data: (1) data driven decision-making, (2) fail fast and learn fast, and (3) common language, which we refer to as a Data Culture, out of necessity and convenience for a collective term.

We extract 24 relevant documents from McKinsey, and 26 supporting documents, and find that culture is an overlooked component of the organization. Management does not assign the value nor attention it really needs as culture is a complex and fragmented invisible force difficult to measure. However, our data also suggest that if misalignment between the underlying culture and the business strategy is a reality, the organization becomes unhealthy and has difficulty achieving strategic goals – such as using data as the base of decision-making.

We use ideas from Edgar Schein with six culture embedding mechanisms for leaders to influence organizational culture. We modify these mechanisms to fit with big data and suggest 18 actions to act on in the 6A framework. The purpose of the framework is to guide leaders on all levels of an organization towards a data culture. We find that cultural change must start at the top, however middle managers are essential in aligning culture on a department level with the overall business strategy.

Keywords: Data Culture, Organizational Culture, Decision-making, Fail Fast, Learn Fast, Common Language, Data Analytics, Big Data, Data Driven, Strategy Alignment, Management Tools, Embedding Mechanisms, Leadership, Data Talent, Data Revolution, Maturity Models

Contents

1. Field Introduction

1.1. Big Data Revolution

Large amounts of data, which previously was left unrecognized, is now turning into a competitive weapon allowing firms to deliver excellent customer-service, develop innovative technologies and recognize undiscovered opportunities in the market. Big Data refers to large amounts of both structured and unstructured information. Structured data includes categorical and tabular data whereas unstructured data covers message traffic inter alia (Knapp, 2014). The concept of big data is something that has been known for years and most organizations today acknowledge the gain and value derived from data if they are able to apply analytics to it (SAS, n.d.).

The accessibility of data is constantly growing. In 2014, people generated more than 2.5 quintillion bytes of data in a single day. We create and leave data behind us in various ways, i.e. via social media and GPS signals (Knapp, 2014, p. 216). The scale of big data is enormous and can be utilized as a valuable and powerful asset for organizations to prosper and compete, if handled correctly (Brown, Chui & Manyika, 2011).

1.1.1. Components

Doug Laney defined big data in 2001 (Patgiri & Ahmed, 2016) through three dimensions to describe data management. However, in the 1950s, prior to calling it big data, organizations were already using the main idea behind basic analytics when examining numbers in a spreadsheet from which they could identify valuable insights and trends (Patgiri & Ahmed, 2016). Though in more recent times we associate new benefits with the term big data such as speed and efficiency. Today, we gather information and run analytics at a much faster pace to reveal value and make decisions rapidly. It is exactly this ability to work at a rapid rate and stay agile that provides organizations with a competitive advantage that businesses did not previously possess (SAS, n.d.).

Laney defined big data as the three V's of big data: *volume, variety and velocity* (Patgiri & Ahmed, 2016). Volume suggests the amount of data that is being produced. It is probably the attribute that is focused on the most when organizations today consider big data, but even though size is a key indicator of big data, the two other attributes are also essential (Russom, 2011). Variety defines the types of formats the data exists in. For example, structured numeric data or unstructured text documents. The last attribute, velocity, refers to the fact that new data is produced constantly. This implies the speed in which data is created, such as different variations of web data generated at a rapid speed, making the volume of data very big and very fast growing. This underlines the challenge of being able to make sense of such large amounts of data and perhaps act on it in real time (Dumbill, 2012, p.1). These V's of big data is the most common way to look at the term. However, there is some controversy and confusion around whether there might be more V's to define big data, and if so, how many and which can be stated to be the correct ones. An example of yet another is veracity. Veracity refers to the accuracy and truthfulness of the huge volume of data. It is being argued that data is worthless if it is not accurate, why this V is important to consider as well (Patgiri & Ahmed, 2016). In retrospective, we find the three V's defined by Laney useful to understand big data in general terms.

1.1.2. Potentials

Big data can provide organizations with the ability to make informed decisions leading to better decision-making, improved operational efficiency, reduced costs, innovation and more (Bean, 2017, p. 2). Every company can benefit from big data, not only leading firms such as Amazon and Facebook that "were born digital to accomplish things that business executives could only dream of a generation ago" (McAfee & Brynjolfsson, 2012, p. 62). Big data can likewise change traditional businesses by transforming its entire business processes, giving them great opportunity to gain competitive advantage (Wamba, Akter, Edwards, Chopin & Gnanzou, 2014). It is through detailed and complex analyses of big data that an organization can identify new facts about customers, operations and markets and utilize that new knowledge to their advantage (Russom, 2011).

1.2. Data Analytics Overlook

“Big data are worthless in a vacuum” (Gandomi & Haider, 2015, p. 140), instead the actual value of big data is first realized when leveraged to drive decision-making. Therefore, the term big data is often used together with Data Analytics as analytics enables meaningful insights from large volumes of data. These concepts are closely related, and both emerged based on the advancement within information and communications technology (Chen in Frisk & Bannister, 2017). Data analytics is the practice where “advanced analytic techniques operate on big data” (Russom, 2011, p. 8) which could be based on for example data mining, natural language processing or sentiment analysis. The overall purpose of analytics is to discover hidden patterns and meaning (Gandomi & Haider, 2015, p. 140) and it is through increasingly advanced algorithms that big data analytics support the advancement in decision-making quality and efficiency (Thirathon, Wieder, Matolcsy & Ossimitz, 2017). This is furthermore supported by Wamba et al. (2014, p. 2) suggesting that organizations indeed create remarkable value as well as enhance its productivity and competitiveness by collecting, storing and mining big data for meaningful insights.

2. Research Area

2.1. Big Data Critique

Big data has become a corporate asset and a determining factor in how organizations compete and thrive in today's digitalized world (Brown et al., 2011). Though, simply collecting big data will not reveal its potential. Where a market for data exists, it is unlikely that big data as a resource is "inimitable, rare, valuable by itself or non-substitutable" (Lambrecht & Tucker, 2015, p.3). Various studies show that initiatives for embedding data throughout operations in an organization often fail (Gourévitch, Fæste, Baltassis & Marx, 2017). A study reported in 2019 that 97.2% of firms are investing in big data and artificial intelligence initiatives, however still experiencing major challenges in treating data as a business asset and becoming data driven as well as gaining competitive advantage (NVP, 2019, p. 14). There are multiple factors indicating why organizations fail on this matter. Generally, organizations are struggling with understanding what the digital era requires and what it means. They are simply lacking the holistic view on what it requires from them as an organization to make use of it (Bughin, Catlin, Hirt & Willmott, 2018, p.2). It is for example very difficult to set up strategic processes to manage the change of becoming data driven and to solve the related challenges in an effective and collaborative way that will yield the best results and lead to good decision-making (Hazan, 2017). Another factor is that it takes the right people to be able to unlock its value and be able to pursue a long-term advantage (Lambrecht & Tucker, 2015). A longitudinal report (Wamba et al., 2014, p. 8), based on three years of research, found that 16% of 1154 articles identified *talent* and *organizational change,* referring to having the right skill-set as well as buy-in from top management, as dominant inhibitors for getting real value from big data. However, finding people with the right skill set can be difficult (McKinsey & Company, 2014).

In the beginning of the big data era, the focus has mainly been on developing and acquiring the right technology. But it is becoming clearer that technology infrastructure is enough, suggesting that organizations are lacking important organizational competences to accommodate for the revolution. It is estimated that 500+ programming languages exist today, and big data and analytics are continuously gaining momentum, illustrating why it is so complex for businesses to keep up and succeed with it (Batistic & van der Laken, 2019, p. 229).

What is required to change? Can you change too much or too little? Recognizing that change in different aspects of the organization is needed can be difficult, yet necessary (Carnall, 2007). This implies that in order to turn big data into a competitive advantage, it is essential to develop new competencies within the firm that goes beyond acquiring necessary tools and software, such as attracting employees who possess the ability to train algorithms (Lambrecht & Tucker, 2015, p. 9) or the ability to train and motivate current employees. The latter, training current employees in new processes and teaching them new skills, will in many cases be possible, however only with the support of individual talents, or champions, with a different way of thinking (McKinsey & Company, 2013). It is important that the existing employees embrace and grasp the new change of making decisions based on data (Watson, 2016) and some employees will also prove to no longer be a cultural fit to the company (DeLallo, 2019, p. 2) without at least the eagerness to learn. Those with no desire to change at all must therefore be replaced (Watson, 2016, p. 8). In addition to creating a sustainable big data team, it is also important that they have the talents with capability to clearly communicate complicated information throughout the different business units (Ariker, Breuer & McGuire, 2014). These individual talents, oftentimes referred to as *translators,* are specialists that can bridge different functions within the company and effectively facilitate collaboration between them. According to a publication by McKinsey, only some companies opt for finding talents that holds more than analytical knowledge and expertise (McKinsey & Company, 2016). Zoher Karu, vice president of global customer optimization and data at eBay, states that being an analytics talent alone is no longer sufficient. Employees must hold plural skills that support the analytics expertise and Karu adds that “I look for people with a major and a minor. You can major in analytics, but you can minor, for example, in marketing strategy” (McKinsey & Company, 2016, p.5). When creating a team with various skills and unique ways of understanding analytics, the organization achieves better prerequisites to identify and solve issues in various areas. The type of human capital that is needed to operate a data driven organization includes data translators translating insights into business value, data scientists ensuring top algorithms, data strategists ensuring future data requirements and a head of analytics driving the execution of the data and analytic strategy (Ariker et al., 2014). Generally, individual talent should be able to identify problem areas, the necessary and right technologies needed, solve them and be able to communicate about them (McKinsey & Company, 2016, p. 5).

2.2. Managerial Demands

We have so far talked about some of the key issues with big data and why organizations struggle with it. But it is also crucial that top management is invested in the change and moves away from making decisions based on gut feeling to be based on data (McAfee & Brynjolfsson 2012) which requires a good understanding of what is needed to assure long-term success with data analytics (Brown, Court & Willmott, 2013). The real potential of big data analytics is unlocked when it is applied for solving insights that was previously solved by intuition. Management is important in this process as it involves knowing what should be looked for and what problems the data can help solve, so the team does not waste time by waiting to see what eventually rises from the data for them to solve (Bowcott, 2017). Data and analytics have changed the entire way of doing business today. This creates new demands to top managers which are, in most cases, without the required capacity to respond (Brown et al., 2013).

Organizations that are doing analytics "just for the sake of doing analytics" (Chin, Hagstroem, Libarikian & Rifai, 2017, p.3) will fail fast and big in this new environment. Top management must come to terms with the fact that having a few digital initiatives and procedures does not compose a digital strategy. It is inevitable that radical changes must be made throughout the organization to fit the new environment (Bughin et al., 2018, p.13). Moving forward, executives need to ensure that they have full awareness of and clarity on what exact business value they are attempting to create, otherwise organizations could potentially do too much too fast resulting in failure (Chin et al., 2017) and not having an approach to the transformation that is agile or manageable enough to undergo such changes (Gourévitch et al., 2017). Fortunately, most companies are aware that it is a critical factor to adapt the organization and implement changes to its procedures and structures in order to succeed long-term. This is a huge determination in who will succeed with data initiatives, as doing well with these new challenges has to be highly prioritized and requires that things should be done differently, so management, first and foremost, must be willing to do things differently and invest in going forward with data (Chin et al., 2017, p. 7). A study found that out of nearly 65 leading firms described as being data mature, such as Mastercard and General Motors, 91.7% of them acknowledge that business transformation and greater agility are driving factors enabling them to gain a competitive advantage (NVP, 2019, p. 9).

Overall, the continuous theme in existing literature is that the challenges for succeeding with big data initiatives is mostly related to management and employees compared to technological challenges (Asay in Comuzzi & Patel, 2016, p. 1469).

2.3. The Culture Problem

Top managers' attitude towards change, or more specifically, leadership style is a very important factor in how well the organization will handle and succeed with changes. According to Schein (2016), leadership is the source to beliefs and values for the rest of the organization and it is crucial that leaders understand the deeper levels of the organization's culture in order to know what to do when challenges occur and, with it, the need to adapt. Leaders will define the culture through behavior and what the leader for example measures on, reward for or assign resources to, as well as the cultural tasks that the leader must be able to handle appropriately is changing with the advancement in technology (Schein, 2016). Employees look towards the leader when they feel overwhelmed, incompetent or insecure and need to be guided or positively pushed in the right direction. Schein argues that change creates learning anxiety which is the fear of no longer doing what is known and feels safe. Instead, doing something that is not known and therefore feels unfamiliar will be perceived as unsafe. The latter, the unfamiliar aspect that comes from change, is accompanied by a feeling of being challenged on one's competencies or position, causing denial and resistance to change. The way of successfully transforming anxiety into a feeling of security while collectively learning is in the hands of the leader, and therefore is knowledge of the culture so important (Schein, 2016, p. 339-340).

Unfortunately, we discover, through existing literature, the role of culture in big data does not seem to be highly prioritized in many organizations. Leaders think of culture as something that will magically happen along the way and not as something that should be highly prioritized and strategically planned for. A leader's mindset on cultural change has been exemplified as “Oh gosh, culture! I'll deal with that once the real work is done” (Bowcott, 2017, p. 6) which fails to acknowledge that culture is one of the most powerful forces in organizations in securing stable and long-term survival (Schein, 1996) and that “the most important predictor of a company's success and ability to innovate is culture” (DeLallo, 2019, p.1) which will dominate who will succeed in making decisions based on data. Instead, the culture should be fitted to suit the new business strategy and prepare the organization on new challenges to come (Bowcott, 2017). When an organization then reaches the level of having a strong culture, it will express itself through engaged employees who are motivated in their jobs and committed to their leaders resulting in higher productivity (Schein, 2016). Though, changing a culture will provide many obstacles and will oftentimes interfere with more than new tasks, such as going from working individually to working collaboratively or changing the power structure in the organization (Frisk & Bannister, 2017, p. 2075). A study from NVP (2019, p. 7), shows that 77.1% of executives have stated that adopting big data initiatives remains a challenge in their organizations. A total of 95% of the obstacles is related to cultural and organizational issues, once again arguing that the early focus on technology and infrastructure is not the predominant issue. The biggest challenges are a lack of organizational alignment and agility, cultural resistance to change and lacking change management (Bean, 2017; NVP, 2019). On the same notion, 69% firms stated that they do not yet have managed to establish a data driven culture due to cultural challenges (NVP, 2019, p. 12).

In our research, we find it difficult to look for literature on how organizations transition their culture to a data driven one, and what this type of culture exactly is. Various articles, hereunder Wamba et al. (2014, p. 24-25), states that future research should focus on developing explanatory and predictive theories by examining topics such as leadership, talent and company culture, all argued to be factors with huge impact on implementing big data into the organization successfully.

According to Comuzzi & Patel (Buhl et al., in Comuzzi & Patel, 2016, p. 1471), it is widely recognized that organizations need substantial guidance when tapping into the potential value generated by big data. Today, *maturity models* (see section 4.1.1.), are the best examples of guidance to organizations. The specific purpose of maturity models is to help organizations become aware of where they are in the process of becoming data driven and identify current maturity levels in different dimensions, implying what areas to improve on when moving towards the final goal of becoming fully driven by data.

3. Research Topic

We look into why management is having difficulty translating data analytics to a competitive advantage and how management can address this through culture development. The immediate obstacle is access to academic literature on a big data culture and a part of this research involves understanding and defining what a big data culture is.

We are interested in collecting white paper publications from companies, such as leading global consultancy agencies, because they are linked to rich data from the real world. This is to accommodate our theoretical development. The main objective is to bridge ideas from organizational management studies with data we extract and to develop a pragmatic solution for managers to use.

3.1. Motivation

In section 2., we account for the largest challenge that organizations are facing right now in the global landscape. Becoming data driven is a matter of survival, at least in a near future, and leaders all over the world will need tools to prepare organizations to accommodate. We believe to have discovered a fundamental factor, overlooked by leaders in these organizations, complicating the transition towards using data analytics effectively. This factor is described as the culture specific to an organization in big data.

We find a surprising lack of focus on culture by leaders of organizations despite overwhelming consensus in academic literature on the importance and power of aligning organizational culture with corporate business strategy.

We want to contribute to the pressing issue by collecting the most important work by both the consultancy industry and scholars in organizational studies to lay down some of the initial groundwork needed to further advance on the ideas of how to successfully build and instill a culture that supports the transition towards data driven organizations.

First, the purpose of this thesis is to develop a generic theoretical framework to be used by managers and leaders in the process of transitioning to a culture that fits with a data driven agenda. We aim to bridge complicated or theoretical ideas found in literature with result-oriented actions and initiatives to be taken by management and leaders.

Second, we strive to provide information and direction on what exactly is needed from a leader to become a driving force in cultural change, as we recognize that mapping the main transition mechanisms might not be sufficient. Managers and leaders must undergo a personal transition as well by adopting new views on the organization as a moldable organism and how they will have to take responsibility and engage in new roles necessary for creating change, and engaging in new roles too requires a change in management style and priorities.

Third, the framework should serve as a starting point for future advancement on the issue. We acknowledge that we will not be able to produce a holistic framework able to fully encompass the entirety of the culture concept and how it translates to data driven organizations. Culture is complex and difficult to measure as an invisible part of an organization, and the reality is that the body of work on the subject is not yet complete enough. However, we do discover a beginning tendency of awareness on the importance of culture in organizations with big data goals, mainly from reading consultancy white papers. On a fundamental level, the aim of this study is to contribute to this development and to shift the awareness to include businesses as well.

3.2. Scope

Being interested in investigating how a solution can help leaders transition to a data culture, involves many underlying areas that potentially could be investigated, which is why we must scope our research area. We do so to determine the most important topics that must be accounted for, for creating the framework and for being able to do a comprehensive study. Areas such as macro culture, subcultures or theoretical organizational typologies, i.e. Miles & Snow (1978), could mean for the effectiveness of the framework, are areas outside the scope of this paper. However, in the paper we do briefly touch upon these topics and reflect on their influence and meanings on the framework. Also, we do not look into how the role of leaders has changed over time, but rather what new demands there are for leaders in today's technological environment. We do however, later in this paper, highlight such areas for future research that potentially could strengthen and add to the value of the framework. We scoped this paper to facilitate the creation of a generic solution with actionable steps for leaders to take. Throughout the paper we refer to our framework as the 6A framework, covering the six A's of each mechanism respectively Attention, Allocation, Acknowledge, Anxiety, Act and Acquire.

3.3. Problem Statement

With the emerging data revolution, organizations all over the world are facing challenges of evolving into data driven corporations. Understanding why the industry has not made better advancements in effectively adopting data analytics is becoming an increasing focal point in organizational studies.

The literature on organizational culture has historically focused on culture as a general term in understanding how culture manifests itself in the organization. However, there is limited work on different archetypes of culture and, more importantly, on organizational culture which promotes and facilitates data driven behavior.

3.4. Research Questions

We formulate three research questions to guide and focus our process:

- What is a culture in a data context?
- What is the role of management in culture transition?
- How can existing ideas from organizational management studies be applied to support a data driven transition?

4. Theoretical Ground

Table 1: Use of Core Literature

Authors	Topics				
	Data Driven Organizations	Organizational Culture	Data Culture	Leadership in Culture	Data Talent
Ariker et al., 2014					x
Baltassis et al., 2019	x				
Bass, 1965		x			
Betteridge & Nott, 2014	x		x		
Bilbao-Osorio et al., 2014	x				
Boughzala & Vreede, 2012	X				
Bowcott, 2017		x		x	
Bridgwater, 2020			x		
Brown et al., 2013				x	x
Buluswar et al., 2016			x		x
Carnall, 2007			x		
Chin et al., 2017		x	x	x	
Comuzzi & Patel, 2016	x		x	x	x
Davenport et al., 2012					x
DeLallo, 2019		x	x	x	
Diaz et al., 2017			x		
Diaz et al., 2018				x	
Drus & Hassan, 2017	x				
Franco-Santos & Gomez-Mejia, 2015					x
Frisk et al., 2017		x	x	x	
Gourévitch et al., 2017		x	x	x	x
Halper & Krishnan, 2013-2014	x		x		
Hazan, 2017			x	x	x
Henke et al., 2016a				x	x
Henke et al., 2016b					x
House et al., 2004		x		x	
Khoshgoftar & Osman, 2008	x				
Leavitt & Bass, 1964		x			
Mayhew et al., 2016				x	x
McAfee & Brynjolfsson, 2012			x	x	x
McKinsey & Company, 2013			x		
McKinsey & Company, 2016			x		
Pettey, 2018			x		
Ritter et al., 2017	x				
Roberts, 2019			x		
Schein, 1996		x			
Schein, 2016		x		x	
Sinclair, 1993		x			
Thirathon et al., 2017			x	x	
Tung & Chatelain, 2018	x				
Wamba et al., 2014				x	
Watson, 2016				x	
Wingard, 2020			x		

This section includes core theory used in our research and development. In section 4.1., we describe what it means to be data driven and the tools available for organizations to understand how well they perform. In 4.2 and 4.5.1., we make use of one author in particular, namely Schein (2016), to define organizational culture and describe six culture embedding mechanisms for leaders to manage culture transition. In 4.3., we collect characteristics for a big data culture from literature, and phrase three main characteristics under one term - data culture. Table 1, above, provides an overview of how we have used different documents.

4.1. Data Driven Organizations

4.1.1. Maturity Models

Maturity Models have been developed in academia as a response to the big data era. There are various types of maturity models targeting different issues or challenges but the overall purpose of these is to identify and review the strengths and weaknesses of an organization. It also serves as a tool for benchmarking, so the company can identify and define a clear direction to obtain its goals (Khoshgoftar & Osman, 2008). Big Data Maturity Models (BDMM) can provide a perspective on the new capabilities required, in terms of how to implement and seize value from them in an organizational setting (Hunter et al., 2009 as cited in Comuzzi & Patel, 2016). BDMMs follow the common traditional structure of maturity models. Bilbao-Osorio, Dutta & Lanvin (2014) states that BDMMs often involve creating an ecosystem consisting of relevant technologies, the management of data, analytics, governance and organizational components (Comuzzi & Patel, 2016). The term *maturity* points towards a state in which the organization is in a good place for achieving their specified goals (Berssaneti et al., 2008 in Khoshgoftar & Osman, 2008, p. 955). BDMMs can help determine where to begin when moving towards becoming data driven and has also been defined as an approach for tracking and measuring organizational progress as well as to identify relevant initiatives to be embedded. Furthermore, some organizations also utilize it as a tool for communicating their big data visions throughout the organization, so every employee has an idea of where the organization plans on going and what it requires to get there.

The fundamental idea behind maturity models and the general reasoning for why an organization should obtain maturity is that "a higher level of maturity will result in higher performance" (Boughzala & Vreede, 2012, p. 307) as the organization will be able to predict possible pitfalls, control its progress and therefore improve its efficiency.

A maturity model is made up of different stages, levels or phases. The traditional maturity models typically consist of five stages ranging from stage one to stage five. Existing BDMMs carry out similar stages and dimensions and are therefore very similar to the traditional maturity models (Drus & Hassan, 2017) which is why we will treat it so. Commuzi & Patel (2016, p.1475) has advanced and added an additional level to the traditional five, being a level zero. Level zero refers to "complete lack of awareness by the organization of the capability of which maturity is being measured" (Becker et al., 2009 as cited in Comuzzi & Patel, 2016, p. 1475). Though Comuzzi & Patel (2016) add that in the design phase of the BDMM, they never came across a total lack of awareness that is characteristic for the maturity level zero. The need for implementing a level zero was also only suggested by one company. However, as expressed in the report, they felt that it should not be taken for granted or assumed that every organization have knowledge around the potential of big data. To encompass a more realistic view a level zero was added (Comuzzi & Patel, 2016, p. 1475). We find a similar idea in other models. For example, a BCG maturity model with five stages, not defined by numbers, but as the following: *lagging*, *developing*, *mainstream*, *state of the art* and a *best practice* level (Baltassis, Coulin, Gourévitch, Khendek & Quarta, 2019, p. 2). Lagging resembles a level zero and is defined as having little to no progress across data capabilities. Developing refers to understanding the organizations own challenges and has started to work on them. Mainstream refers to having average data capabilities. State of the art is doing excellent in different data areas but not being able to manage them cohesively. The latter, best practice, is having obtained advanced knowledge in all dimensions of data capabilities and managing them cohesively (Baltassis et al., 2019). Each stage is often developed focusing on providing the organization with a descriptive or a prescriptive aim or in a twofold manner incorporating both aspects. Some models also focus on comparing how mature organizations in the same industry are by utilizing a mix of qualitative and quantitative data. The descriptive objective is the definition of the current level of maturity in the organization in relation to a specific technology or competence in which the organization can analyze and identify at which level they are currently at. The prescriptive stage refers to rules or steps that the organization must follow to improve its current level of maturity (Comuzzi & Patel, 2016, p. 1469). In example of a prescriptive model, Tung & Chatelain (2018) developed a model for each of five dimensions: *strategy and governance*, *architecture*, *development*, *regulations and ethics*, *user support* (Tung & Chatelain, 2018, p. 4)., implying necessary actions for improving its performance. An example hereof could be in strategy and governance where stage 1. suggests that the organization should focus on organizing and defining its vision of how data and models can support its business outcomes (Tung & Chatelain, 2018, p. 7).

It might seem, at a first glance, that maturity models, especially the more descriptive ones, are only scratching the surface of what it entails becoming data mature or data driven. However, a survey by The Boston Consulting Group (Ritter, Baltassis & Quimet, 2017) exposed a gap between the data capabilities that organizations have and the capabilities they predicted they would have three years prior. The survey revealed low maturity in especially one dimension which was the ability to prioritize data initiatives. This is problematic as the right prioritization will lay out the plan for constant improvement and is key to success. The survey revealed that organizations are choosing big data initiatives randomly, causing "leaders to build capabilities that get a specific analytics initiative off the ground, rather than competencies that over time can be integrated to pursue more advanced and more rewarding initiatives" (Ritter et al., 2017, p. 3). This further means that the capabilities they learn will be scattered and not necessarily transferable to future initiatives. This implies that maturity models so far have been a needed guideline for top managers pursuing big data initiatives and is still the most appropriate tool currently accessible when assessing the maturity of organizational components *or dimensions,* but more action oriented solutions are needed for leaders – and not just top management but at every level.

Though maturity models are widely used and have been presented as a tool and solution for helping organizations respond and assess their organization to be prepared for big data, they also entail limitations that must be considered. First and foremost, there are various types of maturity models, however all developed based on very little documentation and guidelines on how to develop a maturity model that is "theoretically sound, rigorously tested and widely accepted" (Mettler et al. 2010 as cited in Drus & Hassan, 2017, p. 117). The absence of generally accepted standards for developing a maturity model has been argued to limit the actual value and potential of many maturity models (Khoshgoftar & Osman, 2008, p. 957). Maturity models have also been critiqued as being too descriptive in its form and do not actually provide nor describe how to carry out actions for improvement, but rather provide a descriptive model for understanding the organization's current situation (Mettler, 2009 as cited in Drus & Hassan, 2017, p. 957). However, Drus & Hassan (2017) argue that because BDMMs are developed based on previous experiences of the authors in the industry they can be concluded as being reliable, rigorous and entails generalizability.

The function of BDMMs is however still important and needed in organizations. Several reports predict that the big data technology market will continue to grow rapidly. It is therefore crucial that organizations evaluate their current utilization of big data to be able to review how to move forward, manage and leverage data sources and through that gain competitive advantage (Drus & Hassan, 2017).

4.1.2. Cultural Domains

When considering BDMMs at a higher level of analysis it defines different dimensions performance that can be developed across. Comuzzi & Patel (2016) mentions the domains of *strategic alignment, organization, governance, data* and *information technology*. In current maturity models, culture is oftentimes referred to as or included in the definition *organization* and treated on the same level as other dimensions. In this case, the organization domain is categorized by people and culture. People referring to "the extent to which employees within an organization are aware of the potential of big data technology" (Comuzzi & Patel, 2016, p. 1475). Whereas culture refers to "the extent to which organizational culture recognizes big data as an important and trusted capability for an organization" (Comuzzi & Patel, 2016, p. 1475). The aim of the organization domain is to comprehend the view towards big data on an individual as well as collective plan. The maturity level increases, at the individual plan, when employees are being proactive, testing and learning from big data technology and sharing positive experiences with fellow employees. Maturity at the collective level is dictated by the level of trust in results created by big data initiatives throughout the organization (Comuzzi & Patel, 2016, p. 1478). Comparatively the goal of the *governance* domain is to assess if needed organizational structures are established which allow for defining expectations of big data capabilities among other things. Existing literature (Halper & Krishnan, 2013-2014; Radcliffe, 2014; Betteridge & Nott, 2014; Comuzzi & Patel, 2016) differentiates between governance and organization with governance as an expression of the formal structures while organization refers to the individual beliefs, attitudes and emerging organizational norms (Sinclair, 1993). The report by Comuzzi & Patel (2016) argue that their newer take on BDMMs identifies the entire set of domains and considers that all these domains are relevant for pursuing big data initiatives, without prioritizing one over the other. However, the report does perceive that organizations easily can and will fall into the habit of prioritizing only exploiting the technological discipline and underestimating the potential of the managerial domains representing for example culture. It is argued that when this happens the potential of big data will not be accessible and initiatives will continue to be limited. It is further argued that *data* and *information technology* are the most important building blocks of BDMMs as they are what constitute big data capabilities, meaning that it is the data generated by the organization, also referring to the analytics and management of it, as well as the technology that is needed to withdraw the knowledge and value from it (Malik, 2013 as cited in Comuzzi & Patel, 2016, p. 1476).

However, our findings suggest that culture is much more than *just* a dimension or, at the very least, a necessary prioritization that should be planned for and approached strategically. On the same note we wonder if it really is the best use of BDMMs to prioritize every domain equally, relative to what equal means in a real-world setting.

We have the feeling that something is missing. We find traditional literature on organizational culture and documents from leading consultancy firms on big data to indicate that culture is a condition for every other condition to succeed. That a stable culture aligned with the business strategy allows for appropriate behavior and better utilization of other domains. If this is the case, cultural domains should be looked at more holistically, in terms of how they support other domains, and separated by a layer in future models.

4.2. Organizational Culture

The early foundation to the field of organizational studies was laid out by Hal Leavitt, Bernie Bass and Edgar Schein in the mid-1960s (Leavitt & Bass, 1964; Bass, 1965; Schein, 1965). Originally introduced as the concept of organizational psychology, scholars at that time sought to separate elements of social psychology and sociology that dealt with group and organizational phenomena from the already established industrial psychology (Schein, 1996). According to Schein however, early research maintained an individualistic bias as it did not consider organizations systemically and further failed to note that culture was one of the most powerful and stable forces operating in organizations. In fact, so powerful, norms held across large social units are more likely to change leaders than to be changed by them (Schein, 1996, p. 231). Schein coined *culture* as the missing concept in organizational studies in his 1996 article and points to researcher's failure of not taking culture seriously enough.

Throughout literature, concepts similar to organizational culture are mentioned under a variety of names such as *rules of the game*, *root metaphors* or *integrating symbols* (e.g. Van Maanen, 1976, 1979b; Deal & Kennedy, 1999; Gagliardi, 1990; Hatch, 1990; Schultz, 1995 as cited in Schein, 2016, p. 4-5). More importantly, despite the different names and variations in definition and focus, culture mostly covers everything that a group has learned as it has evolved (Schein, 2016, p. 5). Schein further argues a usable definition to be more integrative and dynamic if it is to show how culture forms and evolves in organizations, subcultures, and micro systems (Schein, 2016, p. 5).

In our work, we find the definition included in the fifth edition *of Organizational Culture and Leadership* by Schein (2016) to be the most inclusive and pragmatic one. When we talk about organizational culture throughout the paper, we use the following understanding of culture:

> "The culture of a group can be defined as the accumulated shared learning of that group as it solves its problems of external adaptation and internal integration; which has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, feel, and behave in relation to those problems. This accumulated learning is a pattern or system of beliefs, values, and behavioral norms that come to be taken for granted as basic assumptions and eventually drop out of awareness" (Schein, 2016, p. 6)

For something, such as a specific value to become cultural within an organization, the value must be shared across the organization as a basic assumption, taken for granted to a point where members of the organization become unaware of its existence. Schein describes these basic assumptions as the cultural DNA.

The basic assumptions that revolves around how things should be done, how the mission is to be achieved and how goals are to be met make up for some of the most important and most invisible elements of organizational culture (Schein, 2016, p. 158). The elements of culture provide stability because they define the group they belong to. Culture drives member identity, behavior and interactions between members and tells its members how to be rewarded within the culture (Schein, 2016).

Though statements such as these point to the importance of managing and developing organizational culture in a desired direction, transitioning to a new culture is problematic as it is highly anxiety inducing. Changing important cultural elements means destabilizing the organization – at least until the new values, beliefs and behavioral norms become a part of the basic assumptions and the new cultural DNA. However, cultural DNA is particularly difficult to change because group members value stability as it provides meaning and predictability and can therefore not be changed without altering the group altogether (Schein, 2016).

Even though the cultural DNA of an organization is difficult to change, we find necessary incentives for organizations to do so. We looked at culture related white papers from one of the largest consultancy firms in the world McKinsey with supporting literature from databases such as Harvard Business Review, Accenture, BCG and Forbes (see table 3 in section 5.3.2., data collection) – to better grasp how organizational studies are developing outside of academia and is reflected in the industries. In section 1.2. we described how data analytics is transforming most business processes radically and will continue to in the future, and in section 2.2. we highlighted the gap between management and data analytics which continues to exist because organizational culture is not well recognized and understood by the leaders of industries. The consultancy database and supporting literature reveals it to be a survival necessity to shape and instill an organizational culture which promotes decision-making behavior based on data and openness to experimentation and failure, if a company is to successfully adopt data analytics as a core practice throughout the entire organization. According to Diaz, Rowshankish & Saleh (2018, p. 17), culture can be either a compounding problem or a compounding solution as it should come as no surprise that a data mission detached from the business strategy and core operations will result in failed data initiatives, but if excitement about data analytics is infused in the entire organization, it becomes a source of energy and momentum.

4.2.1. The Three Levels

According to Schein (2016, p. 18), a culture exists and can be analyzed on three different levels: *artifacts, espoused beliefs and values* and *basic underlying assumptions*. These levels imply how visible the cultural element is to observe. Artifacts represent the most visible or observable levels of a culture and describe what can be seen, heard or felt. This includes visible products such as the architecture of the physical environment, the language used, observable rituals and ceremonies inter alia (Schein, 2016, p. 17).

Espoused beliefs and values encompasses the ideals and aspirations of an organization. They are often observed as what an organization claims to value or desires to be. Espoused values are typically formulated in the ideology of the organization. Some organizations might value teamwork while others aspire to think differently. These beliefs and values might undergo transformation and ultimately become a basic assumption if actions based on the belief or value continue to produce successful and convincing results. Only beliefs and values that can be empirically tested and that continue to work reliably in solving the group's problems will become transformed into assumptions (Schein, 2016, p. 19).

All group learning begins with someone's original beliefs and values, and if solutions based on these works repeatedly, the beliefs and values will at some point be taken for granted. The basic underlying taken for granted assumptions describes the final and deepest layer of organizational culture. These assumptions are so ingrained in a social unit and have become taken for granted to a degree, that little variation in the assumption exists within the unit. So, when we talk about shared assumptions, it means that a strong consensus exists across members of a culture. Culture at this level provides its members with a basic sense of identity, defines behavior amongst the members and tells them how to feel good about themselves (Schein, 2016, p. 23), which explains why culture as a concept is so powerful.

When building a culture that promotes data driven behavior, the organization will have to demonstrate that values and beliefs about data analytics can produce repeatable and successful solutions to problems, if these are to be transformed into basic assumptions and to be taken for granted. We suspect evolving and maturing in other domains of big data such as strategy, governance and architecture might become more accessible with the right culture in support.

4.2.2. Macro Cultures

"Macro cultures are nations, ethnics groups, and occupations that have been around for a long time and have, therefore, acquired some very stable elements, or "skeletons" in the form of basic languages, concepts, and values" (Schein, 2016, p. 77). We briefly include macro cultures in this project because we recognize their influence on how the 6A Framework is implemented in situations where broader cultures exist and influence a group of people's ability to engage in shared learning – for example in multicultural workgroups.

The three level model for cultural analysis we account for earlier (section 4.2.1.) can also be used to break down a macro culture. When we visit another nation as a tourist, the artifactual level is what we encounter and see when we travel. The espoused beliefs would be expressed as a published ideology of the nation while its basic assumptions can be identified if we make intensive personal observation over a period of time (Schein, 2016). Collectively, a macro culture can be observed on the same levels as an organization's culture.

In today's business climate, however, organizations are becoming more multicultural. Following this, the need to address different macro cultures of a workgroup to make it more efficient becomes a critical activity. Schein (2016) talks about creating temporary cultural islands for this very purpose. For multicultural collaborations to work, the members must first learn about each other (Schein, 2016). A cultural island is a space in which the rules of etiquette and having to maintain face can be suspended for a period of time to enable mutual learning to occur. The objective is to temporarily eliminate different cultural beliefs and foster group empathy through open and personal dialogue. Then the group can focus on collective learning. Furthermore, a cultural island can be deliberately created by leaders. Schein points to the need for leaders who manage multicultural groups to develop the skills to create temporary cultural island experiences for its members (2016, p. 110).

4.2.3. Subcultures

As an organization evolves, grows and matures it develops *subgroups* in different functions of the organization and those subgroups too develop their own culture (Schein, 2016). We call these fragmented cultures for subcultures, as they exist within the boundaries of the larger organizational culture. The development of subcultures is inevitable for the simple reason that groups of people working in different disciplines and positions are different from each other. For the same reason, it might occur that for example software developers feel that management with no insight to coding makes unrealistic demands about software functionality or value certain aspects of development wrongly. They each exist in different subcultures where different underlying assumptions are at play about what goals are most important and how these goals are best achieved. The existence and rise of different subcultures within an organization is a normal phenomenon and does not become a problem unless the subcultures are misaligned (Schein, 2016). It means that even though different groups of people are placed in different functional areas of the organization, building an effective organization is ultimately a matter of encouraging the evolution of common goals, common language, and common procedures for solving problems across the different subcultures (Schein, 2016, p. 230). This further implies the need for communication and dialogue between the groups to arrive at a shared understanding of different views and agree on how to best proceed (Frisk et al., 2017).

4.2.3.1. Operators, Engineers and Executives

Schein describes three generic subcultures which exist in some form in all types of organizations; *operators, engineers* and *executives*. These are the ones that need to be identified and managed to minimize misalignment. The groups have evolved different subcultures because they have different functions, face different environmental problems, and are often based on different occupational macro cultures (Schein, 2016, p 221).

The operator subculture refers to the "front line" employees who produce and sell the organization's products or services. Schein describes them as operators because what defines this subculture across different organizations and types of work is the sense these employees have, that they are the ones who really run things and are the key to the functioning of the organization. Essential to the operator subculture is its valuing of human interaction. Front line units, meaning the operators, typically learn that communication, trust and teamwork is most important in working efficiently (Schein, 2016, p 221).

The engineering subculture is the group of employees that represents the basic design elements of the underlying technology that supports the work of an organization and knowledge of that technology. These employees design and engineer products and systems and are unique to the other two cultures being preoccupied with designing humans out of systems rather than into them. This subculture views an ideal world as one with machines and processes working in harmony without human intervention (Schein, 2016, p 224).

Last, the executive subculture includes top managers. This group is usually represented by a CEO and an executive team. They see the world from a financial point of view with the necessity of organizations to survive through financial health (Schein, 2016, p 226). As managers rise in the organizational hierarchy, they become more impersonal as they go from managing operators or engineers to other managers. As they further climb in position and responsibility, the units they manage become larger, making it impossible to have personal relations with everyone who works for them (Schein, 2016, p 228). Contrary, founders of organizations or family members who have been appointed to executive positions tend to maintain a more humanistic focus (Schein, 2016, p 227).

Executives must take on an additional role when the organization evolves, as they will have to manage new and growing functions and subcultures. According to Schein (2016, p. 229), the worst examples of culture mismanagement happens when leaders turn over the responsibility for culture management to human resources as subcultures cannot coordinate themselves.

4.2.4. Financial Sustainability

Bowcott (2017) reveals insights from a McKinsey database consisting of thousands of companies around the world that has been monitored and measured on cultural health. The data suggests that companies in the top quartile of the database deliver total returns to shareholders three times higher than the rest.

Consider how culture translates to huge successful organizations such as Apple and how people understand and view them from the outside. At one point in Apple's history, it was almost expected that every new product or service launched by them was bound to bring some level of innovation with it. It is no surprise that a company which encompasses the importance of thinking differently, further manifested by the advertising slogan 'Think different' used from 1997 to 2002, will reflect on its employees and Apple's ability to innovate if this way of thinking has become the norm and a part of the cultural DNA in the organization. According to DeLallo (2019, p.1), the underlying culture is the most important predictor of a company's ability to innovate and creating a suitable culture aligned with the business strategy is one of the biggest levers management can pull.

This provides an explanation as to why especially the large digital native companies have been able to adopt data analytics and has gained a competitive advantage as a result because they have managed to cultivate a test-and-learn culture early on in the big data revolution, where initiatives are allowed to fail on a small scale and the teachings of these failures are used to direct future initiatives and decision-making (Chin et al., 2017). Failing fast is an important attribute of an innovative culture because in reality, most innovations and innovative initiatives fail (DeLallo, 2019). Gourévitch et al., (2017) draws a parallel to software development operations, characterized by encouraging experimentation and even celebrating failure as a source for learning, suggesting that elements of a data culture might already be present somewhere in many digitized organizations, though only to be found in specific subcultures. We define the role of subcultures in section 4.2.3.

The task of building a culture, in which data are brought in to support solutions, where people are comfortable with constant change and where delivering and hearing bad news are seen as part of business as usual (Chin et al., 2017), might be the core of what really sets data driven organizations apart from more traditional organizations and there is nothing to suggest that a company can not be just as structured about culture improvement as improving its financial position (Bowcott, 2017, p. 6).

4.3. Data Culture

Due to the sheer complexity and lack of finding a unique term that defines an organizational culture in a data context in the existing literature, we find it not only necessary, but also convenient to gather various definitions of cultures that implies what it means to have a data driven culture. We do this to find the most apparent and common characteristics of such culture and call it Data Culture, so when we throughout our paper refer to this, it is clear what it entails.

We categorize all descriptions of a similar culture and find three trends; a Data Culture can be observed in an organization by three characteristics: (1) Data Driven Decision-Making, (2) Fail- & Learn Fast, (3) Common Language.

4.3.1. The Three Characteristics

4.3.1.1. Data Driven Decision-Making

We find that some authors do not use a unique term for a data culture at all, but instead hints at what it includes, i.e. “a culture in which data, not guesses, are brought to bear on problems, and where people are comfortable with constant change” (Chin et al., 2017, p. 6) or “a culture in which both large and small decisions are deeply informed by data” (Hazan, 2017, p. 9). The latter author does also refer to it as a “new business culture” (Hazan, 2017). In other articles we find that a data culture is referred to as the process of going from a knowing culture to a learning culture (Buluswar et al, 2016; McKinsey & Company, 2016; Carnall, 2007). This is defined as a culture that moves away from previously being dependent on heuristics for making decisions to becoming a culture that is “much more objective and data driven and embraces the power of data and technology” (Buluswar et al. 2016, p.1). Thiration (2017) refers to an organizational analytic culture which is used to depict organizations that perceive data analytics as useful. Thiraton furthermore states that “organizations with a strong analytic culture tend to support larger investments in analytics assets such as big data, more sophisticated analytic tools, methods, and skills” (2017, p. 777). Some authors refer to it as either an innovative data driven culture (DeLallo, 2019), a data-driven culture (Gourévitch et al., 2017) or a fact based decision-making culture (Watson, 2016) which covers cultures that facilitates driving data based decision-making and the utilization and prioritization of using analytical insights (DeLallo, 2019; Gourévitch et al., 2017). Diaz, Rowshankish & Saleh (2017) discusses the competitive advantage that can be unleashed by a culture if they succeed bringing "data, talent, tools, and decision making together" (p.2). In this article, they do refer to it as a data culture, which, as apparent from this paragraph, is not a commonly used term elsewhere in the literature. They do also state that "data culture is decision culture" (p.2). We discover McAfee & Brynjolfsson refer to it as a decision-making culture which, by making data-driven decisions, enables managers to make better decisions as well as be able to manage better as "you can't manage what you don't measure" (2012, p. 62).

4.3.1.2. Fail & Learn Fast

The characteristic fail & learn fast is by some authors defined as a test-and-learn culture, a data driven test-and-learn culture (Chin et al., 2017; Gourévitch, 2017), a fail fast fail often culture (Wingard, 2020), while it is also just referred to as a fail-fast culture (DeLallo, 2019). Common for the definitions is the focus on learning from mistakes or experiments, "we are trying to move more quickly in learning from failures and moving to the next iteration" (Chin et al., 2017, p. 7), "requiring people to fail fast is one of the most important attributes of an innovative culture (...)" (DeLallo, 2019, p. 2) as well as "embracing a test-and-learn culture that encourages experimentation, accepts - even celebrates - failure, and is always learning" (Gourévitch et al., 2017, p. 7). A general component is that working with large amounts of data requires a company to be able to generate insights and new ideas quickly, be able to test them and from that decide to either continue with it or not. In this process it is important to communicate mistakes or failures early and without shame "because mistakes are seen as sources of improvement for the next iteration" (Chin et al., 2017, p. 6). In addition, Chin et al., (2017) further highlights that perhaps not all units in the organization need to fully adopt this approach, but more so those who work closely with analytics as well as business units and functions that need to acquire ideas or insights from data. We refer to the definition fail & learn fast, as opposed to test and learn, as we find failures happen through testing, experimentation or the like, and it is these mistakes the employees must learn from. Broadly, it is about failing smart, assuming that failures will lead to valuable learning (Wingard, 2020).

4.3.1.3. Common Language

Cultural transition to data culture requires that members of the organization can understand and speak about data. Being able to talk about data enables collaboration. Chin, Hagstroem, Libarikian & Rifai argues "I have lots of people who speak the language of business, and I have no problem finding software engineers who speak the language of technology" (2017, p. 6). However, to find someone who speaks both languages is challenging (Chin et al., 2017). It is stated that as data and analytics is becoming the core of an organization and data is an organizational asset "(...) employees must have at least a basic ability to communicate and understand conversations about data (...) the ability to "speak data" will become an integral aspect of most day-to-day jobs" (Roberts, 2019, p.1). Without a common language for data, it will become challenging and complex to "(...) develop a plan that brings together data, analytics, frontline tools, and people to create business value" (McKinsey & Company, 2013, p.1), and adds that executives should prioritize establishing a common language to maintain focus on goals and getting started with data. "Learning to "speak data" is like learning any language. It starts with understanding the basic terms and describing key concepts" (Pettey, 2018, p.1). Pettey (2018) further states that the ability to communicate the data language is becoming the new organizational readiness factor. Likewise, talking data is not just a temporary skill, it is a "lifelong commitment, so data fluency (where it happens) should be celebrated" (Bridgwater, 2020, p. 1). Trice, 1993 (as cited in Frisk et al. 2017) implies "that communication and dialogue are of critical importance in order to arrive at a shared understanding of different views and ultimately at an agreement on how best to proceed" (p. 2075). This underlines why a common language is an essential characteristic of a data culture, as it, not only in a data context, but in every business aspect, is important to talk the same language in order to work towards the same goals and reach the same understanding. Otherwise, "if there is no common language (...) there will be fundamental communication challenges when using data- and analytics-based solutions" states Pettey (2018, p. 1).

4.4. Talent

Developing the right expertise within the organization is the differentiator in being able to pull insightful meaning from the data collection and execute data driven strategies (Gourévitch et al., 2017). The right talent will find the right technologies and solutions to emerging problems (Nilson as cited in Buluswar et al., 2016). However, when we talk about talent in a cultural setting, it means more than the capabilities of the employees in an organization. Not everyone needs to become a data analytics expert and learn to code, although everyone does need to adopt a less risk-averse attitude (Gourévitch et al., 2017). Talent also extents to employees who do not work with data analytics directly. Everyone in the organization, including frontline staff, will have to learn to use the insights created by data analytics (Chin et al., 2017, p.4) and to become, at least partially, data literate in order to make better decisions in everyday work.

The main challenge of attracting talent remains the scarce amount of talent up for hire (McAfee & Brynjolfsson, 2012). Due to a very specific combination of capabilities, the market lacks specialists of different types (Davenport, Barth & Bean, 2012; Ariker et al., 2014; Comuzzi & Patel, 2016; Mayhew et al., 2016). Furthermore, building talent in a data culture through hiring of expensive new employees does typically not work. Mayhew, Saleh & Williams (2016, p. 11) suggest that a combination of strategic hires, people to help lead analytics groups and especially, equipping and reskilling current employees with quantitative backgrounds to join in-house analytics teams is the most effective route. In addition, strategic acquisitions or partnerships with small data analytics service firms can be valuable in some cases.

This balance between recruiting necessary talent and retraining existing employees to equip them with data capabilities is important for the integration of a data culture (Diaz et al., 2018). To unleash the potential value of big data, organizations must think about talent in terms of value chains and understand that skill and capability links between employees are crucial (Ariker et al., 2014). According to Brown, Court & Willmott, almost any strategic scenario requires “more analytics experts who can thrive amid rapid change” (2013, p. 5). However, there is a need for other different types of talents with extreme specialist skills. There are five general roles to consider (Henke et al., 2016b; Hazan, 2017). Data architects are responsible for building the infrastructure that supports the collection and storing of data; data scientists are needed for their mathematical- and statistical knowledge in combination with programming experience to develop the algorithms and learning systems that will convert data to business intelligence; data translators form the bridge between analytics and business with an understanding of data driven business cases, challenges and basic statistics (Hazan, 2017). The role of data translators has been undervalued in the past, but organizations are in need of talent who can analyze, distill, and clearly communicate the value of analytical insights (Ariker et al., 2014; Hazan 2017). Data engineers are mentioned as the fourth role by Henke et al. (2016b). These are the people who scale data solutions and build products. The first four generic roles combined with skills in cleaning and organizing large data sets (McAfee & Brynjolfsson, 2012), and experience in creating effective user interfaces are particularly powerful (Henke et al., 2016b). In addition, the literature suggests that organizations should appoint a data chief officer. Besides a formal role of managing these types of data specialists, the data chief officer must be an evangelist with the ability to dispel internal reluctance and actively advocate for change (Hazan, 2017). Organizations struggle to create a distinctive culture that can attract the best talent without a dedicated leader (Henke et al., 2016a).

4.5. Leadership

We have previously described various disconnections between data analytics and management in section 2.2. When we talk about data driven organizations and management together, we do so because it is evident from both academic literature and white papers that the root of these disconnections, a missing culture to support decision-making based on data, is caused by managerial practices and leadership. However, at the same time we suggest that the culture problem is solved by the very same leaders and managers causing frictions. But it requires leaders to change the way they think about culture and for them to understand the critical role they play in culture transition. Without the support and commitment of leaders, organizations struggle to implement the desired cultural elements that will make data driven practices efficient. Changing a culture starts by changing the leader (McAfee & Brynjolfsson, 2012; Brown et al., 2013; Wamba et al., 2014; Schein, 2016; Henke, Libarikian & Wiseman, 2016a; Mayhew et al., 2016; Comuzzi et al. 2016; Watson, 2016; Bowcott, 2017; Chin et al., 2017; Gourévitch et al., 2017; Hazan, 2017; Thirathon et al., 2017; Diaz et al., 2018; DeLallo, 2019).

4.5.1. Six Embedding Mechanisms

In this section, we cover how new ideas and values are introduced and embedded in an organizational culture through leadership and how leaders alter a culture through the use of specific tools. Once again, we rely on the work of Edgar Schein (2016) and what he defines as *the primary embedding mechanisms for leaders*. These mechanisms are described as: *"the major "tools" that leaders have available to them to teach their organizations how to perceive, think, feel, and behave based on their own conscious and unconscious convictions"* (Schein, 2016, p. 181). Leaders are able to interact with culture through strategic actions that utilize the mechanisms.

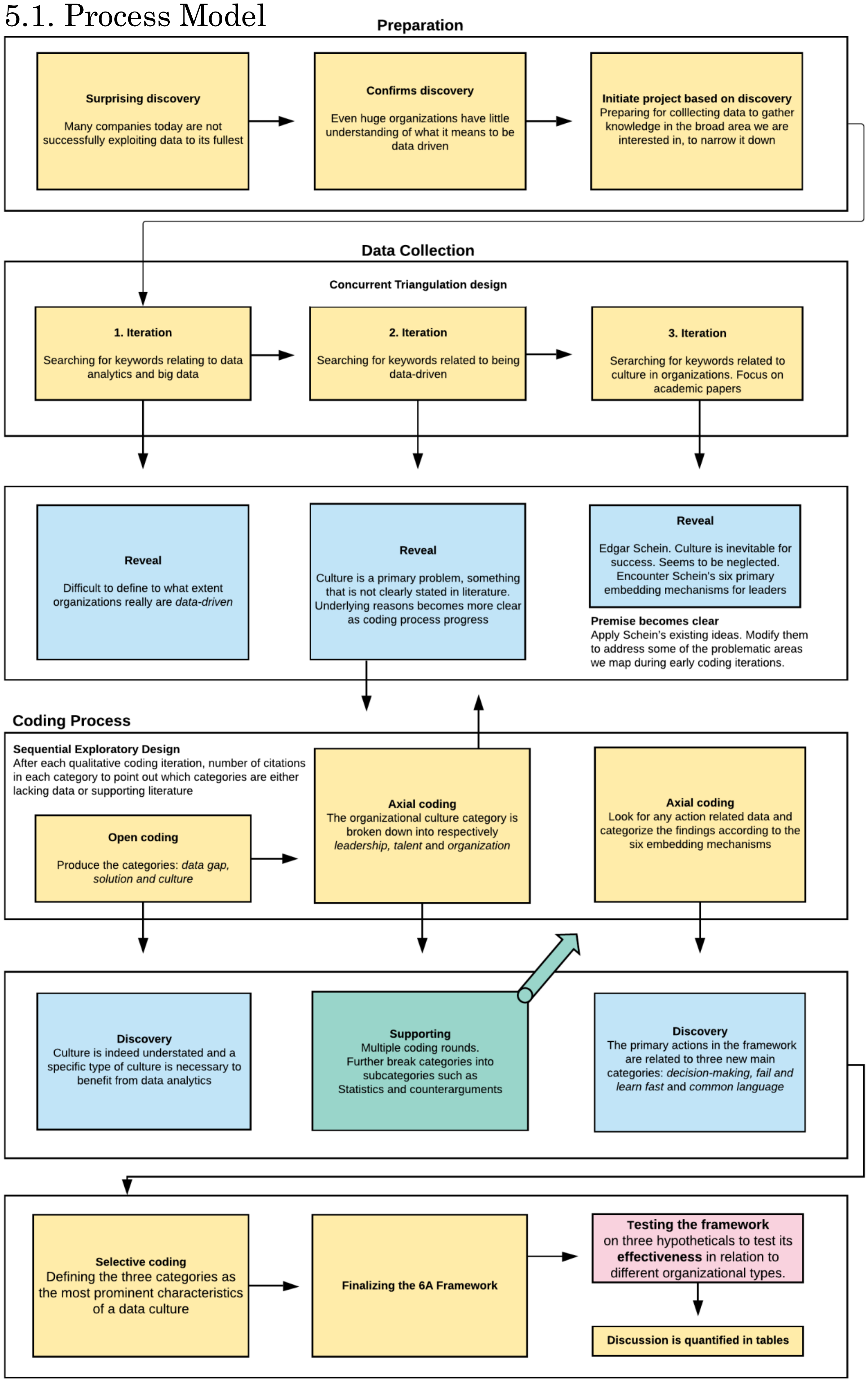
In the table on the next page, we present Schein's six embedding mechanisms for leaders (Schein, 2016, p. 184-195). We use these mechanisms as a foundation to develop our own framework for leaders to use. When Schein talks about culture and the role of leadership in culture, he does so from a general perspective. There is no *true* or *right* culture that fits every organization. The reality is that the right culture for an organization is one aligned with the business strategy. However, with the paradigm shift in business practice, caused by the big data revolution, the need for more generic or homogeneous culture archetypes increases.

Table 2: Six Embedding Mechanisms for Leaders *with explanations* (Schein, 2016)

Mechanism	Explanation
1. What leaders pay attention to, measure, and control on a regular basis	*"What leaders consistently pay attention to, reward, control and react to emotionally communicates most clearly what their own priorities, goals, and assumptions are. If leaders pay attention to too many things or if their pattern of attention is inconsistent, subordinates will use other signals or their own experience to decide what is really important, leading to a much more diverse set of assumptions and many more subcultures."* (Schein, 2016, p. 184)
2. How leaders react to critical incidents and organizational crises	*"Crises are especially significant in culture creation and transmission because the heightened emotional involvement during such periods increases the intensity of learning. Crises heighten anxiety, and the need to reduce anxiety is a powerful motivator of new learning. If people share intense emotional experiences and collectively learn how to reduce anxiety, they are more likely to remember what they have learned and to ritually repeat that behavior to avoid anxiety."* (Schein, 2016, p. 190)
3. How leaders allocate resources	*"How budgets are created in an organization reveals leader assumptions and beliefs (..) As Donaldson and Lorsch (1983) show in their study of top-management decision making, leader beliefs about the distinctive competence of their organization, acceptable levels of financial crisis, and the degree to which the organization must be financially self-sufficient strongly influence their choices of goals, the means to accomplish them, and the management processes to be used."* (Schein, 2016, p. 192)
4. Deliberate role modeling, teaching, and coaching	*"Founders and new leaders of organizations generally seem to know that their own visible behavior has great value for communicating assumptions and values to other members, especially newcomers (..) There is a difference between the messages delivered by videos or from stages settings, such as when a leader gives a welcoming speech to newcomers, and the messages received when that leader is observed informally. The informal messages are the more powerful teaching and coaching mechanism."* (Schein, 2016, p. 193)
5. How leaders allocate reward and status	*"Members of any organization learn from their own experience with promotions, from performance appraisals, and from discussions with the boss what the organization values and what the organization punishes. Both the nature of the behavior rewarded and punished and the nature of the rewards and punishments themselves carry the messages. Leaders can quickly get across their own priorities, values, and assumptions by consistently linking rewards and punishments to the behavior they are concerned with."* (Schein, 2016, p. 194)
6. How leaders recruit, select, promote, and excommunicate	*"One of the subtlest yet most potent ways through which leader values get embedded and perpetuated is the process of selecting new members (..). This cultural embedding mechanism is subtle because in most organizations it operates unconsciously. Founders and leaders generally find attractive those candidates who resemble present members in style, assumptions, values, and beliefs (..). "Fitting in" becomes a value in its own right."* (Schein, 2016, p. 195)

5. Methodology

5.1. Process Model



Saunders, Lewis & Thornhill (2016) and Clough & Nutbrown (2012) distinguishes between the term methods and methodology. Methods is defined as the techniques and procedures utilized to acquire the data, referring to the type of data collection, i.e. questionnaires, interviews as well as other quantitative and qualitative techniques. It is a component of the research and a tool for answering the research questions. On the other hand is methodology. Methodology refers to the reasoning for the research and analysis and how new knowledge is perceived and handled.

This section will describe the methods applied throughout this paper and account for the process when answering our research question. This includes our research philosophy, data collection as well as an evaluation of the validity and reliability of the methodology. In addition, we reflect on the limitations to our strategy.

5.2. Philosophy of Science

Research philosophy refers to the development of new knowledge and encompasses our assumptions and beliefs about the world and how that reflects our chosen strategy and methods for conducting research. Saunders et al. (2016) presents five types of research philosophies: positivism, critical realism, interpretivism, postmodernism and pragmatism.

We make several assumptions throughout our paper. Some of which we are perhaps not even aware of or do not immediately recognize. Such assumptions could be about human knowledge, the reality we encounter in our research, or how our own values influence our research process. These assumptions share how we understand our research questions, develop our process and how we interpret our findings. It is essential to have an understanding of the research philosophy, as this awareness of our philosophical commitments, i.e. our choice of research strategy, will be reflected in what we do and how we understand what we are investigating.

We strive to generate value applicable to organizational practices by operating problem-oriented and from a pragmatic understanding. More specifically, we aim to connect some of the important dots in literature and make a difference to real world practice by offering an action based framework, called 6A, to guide leaders when transitioning into a culture that can leverage from big data. The framework is developed theoretically and built on existing ideas provided by Edgar Schein and his work on organizational culture and leadership. We modify these ideas to fit in data related contexts and include a body of white paper documents as secondary data when defining the data contexts.

In a pragmatic view, we consider theories, concepts and findings in terms of what role they constitute as well as what consequences they imply in specific contexts, rather than considering them in its abstract form (Saunders et al., 2016). We claim that concepts are only relevant where they support action and knowledge is gathered to create actions that can be carried out in real life (Kelemen & Rumens, 2008 in Sanders, Lewis and Thornhill, 2016).

5.3. Research Design

5.3.1. Research Approach

The research approach is an expression of identifying the purpose of our research. It refers to how we are going to answer our research question and what our overall purpose for answering the question is. In addition, how we formulate our research question is an expression of the type of study, which either can be exploratory, descriptive, explanatory, evaluative or a combination of these (Saunders et al., 2016).

Throughout our paper we are aware of being open to new findings, constantly challenging ourselves by asking new and open questions in which we continue to gain new knowledge. This approach originates from *exploratory research*. We seek to get a better understanding of an existing problem that may not have been studied much at all and to offer our insights and add new knowledge meanwhile. The exploratory approach does not usually end with a definite conclusion. Instead we point to the things we are still unsure about and define important focal points moving forward.

It is important that we are prepared to change and adapt our process in a way we did not think of, undergoing the process of collecting new insights. Such pivots happen several times, where we must adapt to a new direction while remaining flexible. This is exactly what the exploratory approach requires, as flexibility and adaptability to change is key (Saunders et al., 2016). We begin with a broad focus, illustrating how we initially assess knowledge widely, which then becomes narrower as the research progresses, enabling us to dissect and define at later stages.

Our research approach is however not only exploratory but is rather a combination of exploratory and evaluative. The purpose of *evaluative research* is investigating to what degree something works well. It is often the case in evaluative research designs that researchers are interested in understanding the effectiveness of something in an organization, i.e. a business strategy, process or initiative (Saunders et al., 2016, p. 176). In our research design, we have been interested in assessing how well data maturity models up until today have worked as helpful tools for organizations. We further evaluate our own tool, the 6A framework, in a theoretical discussion against three generic types of organizations. The purpose of this process is to identify potential key issues in our solution, allowing future researchers to use and build on our evaluations.

5.3.2. Data Collection

There are various approaches to collecting data when working exploratory; in-depth literature search, interviewing experts or focus group interviews. Generally, by adopting an exploratory approach, we rely on the data to help guide the stage of the research. Therefore, we must be open to let the data illustrate important factors to be considered that could otherwise not have been considered before they appeared.

Our specific research problem does not suggest one particular type of knowledge or method that should be applied (Saunders et al., 2016). Instead, we find there are multiple ways of answering our research questions sufficiently. In this paper, we use in-depth literature search as our primary way of collecting data. We collect 50 documents over two data collections; a primary and a supporting. We extract from databases of leading corporations in finance and consultancy, such as McKinsey and BCG. We access white paper publications because they typically rely on expert knowledge and are developed with large amounts of data in support. All collected documents are published between 2010 and 2020. Table 3 shows an overview of the two collection processes.

Table 3: Data Collection

Primary Collection			
Database(s)	**Documents Year**	**Sample Size**	**Extracted Pages***
McKinsey	2020	2	11
	2019	2	11
	2018	2	32
	2017	4	33
	2016	6	71
	2015	2	11
	2014	2	8
	2013	2	17
	2012	0	0
	2011	1	12
	2010	1	13
Total	**2010-2020**	**24**	**219**
Supporting Collection			
Database(s)	**Documents Year**	**Sample Size**	**Extracted Pages***
Boston Consulting Group, Accenture, Forbes, Entrepreneur Europe, TDWI, Harvard Business Review, NVP, World Economic Forum	2020	5	45
	2019	2	22
	2018	3	24
	2017	4	26
	2016	5	23
	2015	0	0
	2014	2	21
	2013	1	15
	2012	2	11
	2011	2	39
	2010	0	0
Total	**2010-2020**	**26**	**226**

*** These are estimated pages we extract. In some instances, we only extract some document parts**

5.3.3. Research Strategy

Our research strategy is rooted in *documentary research* in combination with *grounded theory* as our thesis is theoretical, with the purpose of developing a conceptual framework that is grounded in data (Strauss & Corbin, 1990). A documentary research method refers to the analysis of relevant documents that holds information about the area we are interested in (Bailery, 1994 in Ahmed, 2010, p. 2). This method is often used alongside another research strategy, in our case grounded theory. We are using outside sources and documents which are considered to be secondary data and can include both raw data and published articles such as reports, journals and newspapers. These are utilized to support our arguments and viewpoints, though we must be aware that the documents "were collected initially for some other purposes" (Saunders et al., 2016, p. 316). It is up to us as researchers to collect enough data to be able to scope our research design and it is important that we are critical in evaluating the quality of the data. Though, while we need to be extra attentive to the quality of using documents for research purposes, following a documentary research strategy can provide a comprehensive and rich data collection for us to analyze (Saunders et al., 2016).

We collect and analyze data systematically and through several iterations (Strauss & Corbin, 1990). Our analysis begins at the very first data collection as each iteration is used to direct the next (Strauss & Corbin, 1990). The first collection was carried out by searching for keywords relating to data analytics and big data to further scope our knowledge on the topic. The collected data from various white paper databases (table 3) have provided us with a grounded and realistic view of current situations, while we use theory driven academic work in support. In the first collection iteration, it is revealed that even though companies describe themselves as *data driven*, it can be difficult to define to what extent they really are. And more importantly, even organizations who are already invested heavily in data analytics are challenged in numerous areas.

We continue our documentary research strategy and use specific keywords relating to *data driven* when further collecting data. It is revealed to us that culture is a primary problem - something not clearly stated in the literature. We then begin our coding process and in the first round of open coding we produce the obvious categories from read materials. The purpose of open coding is to give us new insights and conceptualize our findings (Strauss & Corbin, 1990, p. 423). We look for differences and similarities in the literature. This process generates three categories: *the gap, solutions* and *culture*. The gap category is created to look for how, where and why a supposed gap exists between organizations and being data driven. The solutions category is created to look for existing solutions on this subject. Culture category contains anything related to culture in organizations. We further explain these categories in the coding rules table (table 4, section 5.3.3.1.) later in this section. Any time we either find new categories or knowledge on existing ones, we create and update the coding rules. In that sense, these rules become an alignment tool when we both are coding.

We discover that culture is indeed understated in both the literature and in its prioritization by real organizations. We also find indications that a specific type of culture is necessary if organizations are to benefit the most from data analytics. Instead, the literary focus is increasingly on providing organizations with stage-models for becoming more data driven, mainly maturity models. However, we find that culture is not a clear element in these solutions. As previously identified in section 4.1.1., maturity models are found to be too descriptive and not providing actual applicability.

We continue building knowledge and search for keywords relating to culture in organizations. This process is focused on collecting academic papers. We identify the work of Edgar Schein through an extensive literature search. He specifically points towards culture as being an inevitable factor in organizational success, which seems to be neglected. We encounter Schein's six primary embedding mechanisms for leaders as presented in the theory section 4.5.1. The premise for this project then becomes to apply Schein's existing ideas and modify them to address some of the problematic areas we map during early coding iterations. As apparent from this process of gathering different types of knowledge, we did not assume one objective truth to be true, but instead we acknowledged that we were dependent on a level of subjectivity, in order to be able to develop specific categories that later had to become practical solutions applicable to the reality we discovered through read materials.

Through axial coding we begin to relate our categories to each other by identifying the main categories of organizational culture. We do this by breaking down our core themes which we establish through the data collection processes. The organizational culture category is broken down into respectively *leadership, talent* and *organization (*table 4, section 5.3.3.1.). In the leadership category, we are interested in how leaders embed basic assumptions into a culture and how the role of the leader fits into cultural development. Talent is an expression for human capital and identifying the need for human data capabilities. The latter category, organization, establishes how culture is expressed in an organization, the role of an organization in culture transition and how culture impacts big data practices in the organization.

We have multiple coding rounds where we further break down these three categories into subcategories (table 4, section 5.3.3.1.) such as *statistics,* containing quantifiable data, and *counterarguments,* collecting any arguments that contradicts the given category or challenges our understanding.

We are far more interested in practical outcomes, rather than creating abstract solutions. Therefore, in the next axial coding round we look for any action related data and categorize the findings according to the six embedding mechanisms. Up until the very finished framework, we continue to look for new articles and new data, constantly challenging our framework and findings compared to new knowledge.

5.3.3.1. Table 4: Coding Rules

Coding Category	Definition
Business	
Organizational Change	From an organisational/business aspect; how an organization changes, why it is important to change, adapt and be agile.
Value Creation	How value is created in an organization and why is it important to innovate and create value in new areas within the organization. Key sentences about the need to harvest potential value in order to succeed and grow as a business.
Data	
Big Data	Key sentences highlighting either technical or practical aspects of Big Data: i.e. definitions, explainings or benefits.
Data Analytics	Key sentences describing analytics, how you use analytics to become data-driven and what it means to be data-driven (using data analytics).
Culture	
Organizational	Key sentences defining what an organisational culture consists of (both related to the more traditional definitions and data culture definitions).
Leadership	How leaders embed basic assumptions, or how leadership fits into organisational culture, top-down approach, including change management/change managers, how to inflict and manage change programs and projects in the organization.
Talent	Human capital, Human data capabilities, e.g. identifying talents within the organization or recruiting new talent that matches the data culture.
Problem Area	
Data Gap	Key sentences or important examples (not including mundane examples) of how, where and why there is a disconnect in organisations and 'being data-driven'. This would for example include gaps of Big Data and/or Culture.
Culture Challenges	Any challenges, difficulties or specific problems surrounding organisational culture, creating or integrating a culture. Typically alignment of subcultures with company DNA.
Business Challenges	Any challenges, difficulties or specific problems surrounding organisational change or creating value within the organisation. E.g. why it is challenging for organisations to adapt to disruptive innovation - or why it is hard to create value internally.
Solutions	Could be maturity models, guides, step-by-step approaches etc. Anything stating that by following a specific approach it could help the organisation e.g. becoming more data-driven.
Methodology	Includes useful method references, method inspiration from other studies or examples of how to write sections of methodology.
Useful Quotes	Good quotes about anything outside of scope. Could be used for saving useful references within a text or if a strong quote is hard to place in other categories, yet still useful.
Subcategories	
Statistics	Any key numbers, models etc. that helps define or underline the given category.
Counter	Any argument that contradicts, challenges etc. the category or something we know challenges or contradicts our understanding.

We discover that the primary actions in the framework are related to three new main categories: *decision-making, fail & learn fast* and *common language*. It is in the last round of selective coding we define these three categories as the most prominent characteristics of what we call a data culture. This finding happens at a late stage of our research, where we gather all our categories and apply theory into making core categories (Strauss & Corbin, 1990) and finalize the 6A framework.

5.3.3.2. Strategy Limitations

Our research initiated from a surprising discovery, suggesting that a lot of companies today are not successfully exploiting data to its fullest. Attending a big data workshop at Copenhagen Business School we find that even huge organizations in Denmark have little understanding of what it means to be driven by data. Initiating a project based on a doubt or a surprising fact (Saunders, Lewis & Thornhill, 2016, p. 144) is very typical in *action research*. Action research is an iterative process to develop solutions to "real organizational problems" (Saunders, Lewis & Thornhill, 2016, p. 189) by using different forms of knowledge both quantitative and qualitative. We are aware that an action research strategy is a better fit, as we attempt to create a practical solution to a practical challenge. However, due to the circumstances of the COVID-19 lockdown (see Appendix 1.), we have not been able to actively cooperate and work with members of an organization. The main reason for engaging in action research would have been to work alongside real leaders and evaluate the 6A framework against real situations.

We find that conducting documentary research alongside a grounded theory strategy (Saunders et al., 2016) still enables us to modify an existing framework by expanding and uncovering differences discovered in newer literature (Charmaz, 1996). We follow a very structured coding process respectively undergoing open-, axial- and selective coding. "Grounded theory coding generates the bones of your analysis" (Charmaz, 2006, p. 45) and we illustrate how we have selected, separated and sorted the data while integrating our findings analytically in our framework. As we from the beginning of the coding phase created categories and later refined and added to them, we were on an on-going basis trying to make sense of the views and actions from different perspectives. We gather them to make sense of the issue we are interested in (Charmaz, 2006). The digitalization of data has further increased the scope for documentary research as we can access and gather data from around the world, providing us with a considerable amount of information to base the design of our framework on (Saunders et al., 2016).

When talking about limitations to our strategy, we must mention the use of secondary data. According to Saunders, Lewis & Thornhill (2016, p. 320), accessing secondary data can be difficult as it could be lacking authenticity or be of low quality, which is why the researchers must remain critical and attentive to the data. We must constantly evaluate whether the data we collect is useful for our purpose and accurate enough. However, the utilization of secondary data has benefits as well. It provides us with the possibility of comparing data in a more general context and it often encompasses statistics or other data gathered from studies. Also, as was the case for us, secondary data can lead to discovering new things that previously was not accounted for or was unforeseen prior to reading and comparing the data (Saunders et al., 2016). In addition, if the researchers perform a comprehensive search for literature it is possible to find a lot of data and perform an extensive project.

5.3.4. Reasoning Approach

It is important to be aware of our approach to theory development, which is an expression of how we as researchers make use of existing theory to draw conclusions, form predictions or create and build solutions (Saunders et al., 2016). According to Saunders, Lewis & Thornhill (2016), three approaches to reasoning exist; deductive, inductive and abductive.

In our research, we naturally adopt *abductive* reasoning. We are working abductively as there are plenty of existing theories regarding the topic of both culture, big data, organizations, tools for measuring maturity in data capabilities and so on. Though with limited information and work in the context we are exploring, we modify Schein's existing tools for cultural instilment to fit the data culture as a result. Abductive reasoning is the reasoning approach that combines deductive and inductive reasoning. It alternates back and forth moving from theory to data and data to theory (Suddaby, 2006 in Saunders et al., 2016, p. 148). A very apparent factor in abductive reasoning is being open to discovering a surprising fact, both in the beginning that can lead to the entire research area, as we experienced, but also being able to uncover and adapt to surprising facts that can occur at "any stage in the research process, including when writing your project report" (Saunders, Lewis & Thornhill, 2016, p. 148).

The inductive element of abduction is most present in our process, as we collect data to explore a specific subject and generate or build theory, in the case of a conceptual framework. Although we are not testing our framework through subsequent data collection as apparent in typical abductive approaches. Generating theory refers to the incorporation of applying existing theory where it is appropriate and from that, either generate a new theory, solution or modify an existing one. Since we are not solely analyzing and reflecting upon existing theoretical themes which the data suggests, we, by applying an abductive approach to our research, are building a solution that is modified from combining existing literature and modifying it to be applicable in the fitting context of our research. It can be argued that the difference between inductive and abductive reasoning is subtle, though an abductive approach focuses on a cause and effect relationship whereas induction looks for defining general rules (Saunders et al., 2016, p. 145). As previously established, we do not seek to generate law-like rules, but instead we aim to discover what is required to successfully build a culture that can facilitate and amplify the effect of using big data technologies. We are interested in bridging the gap between data analytics and the role of management through culture transition.

5.3.5. Qualitative and Quantitative Research

This thesis adopts a *mixed method* approach for collecting data. This method is a branch of multiple methods research, which implies that it uses both quantitative and qualitative data collection techniques (Saunders et al., 2016, p. 165). From a pragmatic view, it comes naturally to us that we make use of both qualitative and quantitative data as we in our philosophical position see it as unhelpful to differentiate and choose. Instead, we view the data in accordance to undertaking our research, no matter its form or structure but rather if it is important and applicable (Tashakkori & Teddlie, 2020 in Saunders et al., 2016).

Combining quantitative and qualitative data is defined as a concurrent triangulation design (Saunders et al., 2016, p. 170). Triangulation refers to using more than one method to collect data for developing a comprehensive understanding of our topic. Through concurrent mixed method research, we use data simultaneously in the same phases, which provides us with a richer, more comprehensive and comparable data collection. We mainly use qualitative data but are aware of applying and understanding various quantitative data, i.e. statistics, to be able to understand the extent of specific issues, such as how many organizations are struggling with recruiting the right talent for big data. By applying quantitative data to our qualitative data, we get supporting numbers to help scope the investigated problem.

We use the software NVivo to carry out our open-, axial-, and selective coding processes. We code each document on a sentence level. This meticulousness gives us a good overview of what articles are concerned with what topics. NVivo is a software that allows for extensive and systematic analysis of qualitative data and which we were taught to use as a part of our master program.

Our process, when using NVivo for coding, follows a sequential exploratory design. Sequential mixed method research involves more than one phase of data collection and analysis, and in the exploratory design, a qualitative method is first used followed by a quantitative (Saunders et al., 2016, p. 171). After every qualitative coding iteration, we use the number of citations in each category to point out which categories are either lacking data or supporting literature. We are able to do this several times until we are satisfied with the balance of data, codes and literature in each category or have exhausted the category. In short, by following the qualitative method supported by a quantitative, we are able to expand and elaborate on our findings until we reach a comprehensive data foundation. The advantage of combining both qualitative and quantitative either in a concurrent triangulation or sequential design is that it leads to greater confidence in our conclusions when one method explains and another supports (Saunders et al., 2016).

As we reach the development stage of our framework, we apply the idea of probing. Though we are aware that we are not actually conducting interviews by asking probing questions, we make sure to engage in critical discussions with relevant people, such as our project supervisor. By undertaking a critical approach to our own framework development – by asking questions such as "could this have been done another way" or "what is the connection between x and y" (Saunders et al., 2016) – we identify focal points several times and are able to address them before they might become problematic.

5.3.6. Time Horizon

Saunders, Lewis & Thornhill (2016) distinguishes between two types of time horizons: cross-sectional and longitudinal studies. The time horizon is an indication of whether research intends to study a particular point in time or give a representation of something over a longer period. In our research, we are interested in our subject at a specific point in time. We do not look at, in example, how the role of leaders has changed over the last decade but rather how the change in technological environment has put up new and current requirements to the leaders of today.

5.3.7. Validity and Reliability

Saunders, Lewis & Thornhill (2016) states that it is unlikely that any researcher can be sure of the answer to the research question being correct. Instead, the researcher should seek to reduce its possibility of being incorrect. Two factors must be accounted for in the research design when increasing the possibility of being correct: internal- and external validity and reliability.

5.3.7.1. Internal and External Validity

In general, validity is an essential "criterion for evaluating the quality and acceptability of research" (Burns, 1999 as cited in Zohrabi, 2013, p. 258). *Internal validity* refers to whether the findings demonstrate what is intended. It is an expression of how confident we can be in our findings. To increase the internal validity of our research design, we, as previously established, applied a triangulation method. This method is stated to be a way to "boost internal validity of the research data" (Zohrabi, 2013, p. 255). We are using triangulation in the form of a mixed method study to strengthen the uncertainty and weakness that otherwise can come from only collecting data through one technique. Instead, as we are collecting information from a variety of sources, as apparent from table 1 and 3, and collecting data with the purpose of supporting other data, we are increasing the likelihood of our findings being correct. However, we are not only looking for data that can confirm what we already know. We seek to increase the validity by generating knowledge and building on our understanding when we include articles from different databases, of different opinions and with varying key themes. In addition, by ensuring we have enough literature to each category in NVivo, we increase the validity of measuring what we intended to, as we constantly make sure we keep within the scope and have enough theoretical knowledge to each category.

External validity refers to how generalizable our findings are and if the findings are equally applicable to other organizations, industries etc. outside of what we examine in our paper (Saunders et al., 2016, p. 204). In our research design we utilize both qualitative and quantitative data. Though the level of generalizability is a general concern in qualitative studies, especially if based on a small sample size. We use data from large consultancy databases, based on expert opinions and on studies of hundreds of different companies (thousands in some cases) in areas relevant to us. This increases our external validity though we acknowledge that the 6A framework should be viewed as a starting point for future development rather than being applied in organizations as is. However, we do still consider the framework to have a level of validity, as we through our later discussion test it against three generic hypothetical organizations. The characteristics we have created each hypothetical from are visualized in table 5 on the next page.

Table 5: Conditions when developing hypothetical organizations

Hypotheticals	
Attribute	Condition
Company Size	Integer (i.e. 10000)
Financial Resources	Weak – Moderate – Strong
Risk Tolerance	Low – Medium – High
Bureaucracy	Low – Medium – High
Management Characteristics	Humanistic vs. Impersonal (e.g. reward, role model)
Data Capabilities	Weak – Moderate – Strong
Flexibility	Low – Medium – High (not able vs. able to change fast)
Stability	Low – Medium – High

The three hypotheticals are based on generic characteristics to resemble organizational types in the real-world. By using general traits, such as company size or financial resources, we are able to discuss how general traits impact the effectiveness of the 6A framework. We are aware of the fact that studying organizations and the effect of management is too compound and multi-faceted to be reduced into making law-like rules applicable to all organizations. However, given the level of abstraction in the framework, with six very different tools and 18 actions suggested for three data culture characteristics, we assume that the dynamicity translates to some extent if the framework is tested on real organizations with similar characteristics.

5.3.7.2. Reliability

Reliability deals with the consistency and replicability of the study. It refers to how our selected data collection techniques and how we conducted the analysis affects to what degree it would be possible to produce and conclude similar findings (Saunders et al., 2016, p. 203). We are very attentive to consistency when setting up processes, doing comprehensive searches for existing literature, following coding rules, coding on a sentence level as well as testing our findings against three generic hypotheticals. We are attentive to consistency to increase the likelihood of others being able to conclude similar findings. Though it is important to keep in mind that given the qualitative nature of our study, with a limited body of literature on our main topic, a direct replication would not necessarily produce the exact same results.

We also constitute action rules and guiding principles to ensure consistency when developing the framework. The principles are expressions of what the framework *should be* and the action rules are to make sure that each action is linked to one of the three characteristics, that each dimension has three actionable steps, that each action sentence begins with a verb to include an action component and that each action sentence should be able to be finished by the implication.

Table 6: Action Rules

Rules	Description
Rule #1	Each mechanism should have three actionable suggestions
Rule #2	Each action should be linked to only one of the three characteristics
Rule #3	Each action sentence must begin with a verb as the action component
Rule #4	Each action sentence must be able to be finished by the implication

6. Analysis

In this section, we present the 6A framework and its components. Afterwards we explain each embedding mechanism in a data context. We provide further documentation for development and the rules and principles we follow.

6.1. 6A Framework

Figure 1: The 6A Framework. A data culture transitioning tool for leaders at all levels

Data Culture	Characteristics			
	Decision-Making	Fail Fast	Common Language	
Mechanisms	**Leader Actions**			**Implication**
Attention Consistency in attention	1. Get in the habit of systematically asking data related questions	2. Establish ongoing informed conversations with top decision makers	3. Use big data tools consistently to create a common language	To establish clear expectations
Allocation Allocate financial resources	1. Budget for data-driven projects and experiments in the business units	2. Consider that many data efforts will fail and allocate accordingly	3. Budget for data literacy training and ensure the necessary skills in the workforce	To message what is financially valued
Acknowledge Reward and recognize	1. Reward data behavior and early success at every level. Consider intrinsic rewards	2. Accept failure and acknowledge insights from failures	3. Provide people in the organization with data about their own performance	To motivate people and incentivize
Anxiety Response to crisis	1. Demonstrate control of the problem with data use	2. Reduce anxiety of failing	3. Implement data processes as solutions in crisis time	To convince people to change
Act Role model	1. Display visible and audible public behavior when making data based decisions	2. Allow yourself to be overruled by data and show what you learned	3. Advocate actively for change and articulate a change story	To communicate cultural DNA
Acquire Recruit and reskill	1. Strike the appropriate balance between injecting new employees and transforming existing ones	2. Teach people to fail-fast and learn-fast	3. Improve data literacy across the entire organization	To build a foundation of knowledge

The main objective of the 6A framework is to provide an approachable overview of how leaders can develop the three organizational characteristics that make up a data culture. We include 18 actions for leaders to take, six to each characteristic, and organize them according to six embedding mechanisms. Embedding mechanisms are concrete tools, or *ways*, for leaders to facilitate cultural change in an organization. Each mechanism has a distinct key implication when used.

6.1.1. Explanation of Mechanisms

6.1.1.1. Attention

What leaders consistently pay attention to communicates their own priorities, goals and assumptions. It is a way for the leader to set expectations to data behavior. Consistency is key, as subordinates will misinterpret inconsistent signals and decide what is really important for themselves (McAfee & Brynjolfsson, 2012; Mayhew et al., 2016; Schein, 2016; Watson, 2016; Diaz et al., 2018; Bague et al., 2020 & Qlik and Accenture, 2020).

6.1.1.2. Allocation

What leaders allocate resources to sends a strong message of what is financially valued by the organization. Prioritizing data- training and projects in the business units will create a better understanding of what investments are valued by the organization to achieve its data strategy (Carnall, 20017; Brown et al., 2013; Schein, 2016; Chin et al., 2017; Thirathon et al., 2017).

6.1.1.3. Acknowledge

How leaders set up intrinsic- and extrinsic reward systems is a way to acknowledge data behavior and define what success looks like in the organization. It is useful when motivating and incentivizing members of the organization by rewarding desired behavior so the reward itself carries the message (Carnall, 2007; McAfee & Brynjolfsson, 2012; Ross, Beath & Quaadgras, 2013; Franco-Santos & Gomez-Mejia, 2015; Dhawan, 2016; Schein, 2016; Bowcott, 2017; Treder, 2019).

6.1.1.4. Anxiety

How leaders reduce anxiety in turbulent situations can be a strong motivator for new learning. If the leader manage to reduce anxiety in a stressful time using big data ideas, members of the organization are much more likely to reuse the solution to avoid anxiety in the future (Carnall, 2007; Baldoni, 2011; Schein, 2016; Bhatia, 2017; Gillaspie, 2018; Schiefelbein, 2017; Bague et al., 2020; Nichols et al., 2020).

6.1.1.5. Act

How leaders display audible and visible behavior is an effective way of communicating assumptions about data. Members of an organization will observe and copy public behavior from managers to reinforce existing assumptions or adopt new ones (McAfee

& Brynjolfsson, 2012; Mayhew et al., 2016; Schein, 2016; Watson, 2016; Bowcott, 2017; Hazan, 2017; Diaz et al., 2018; DeLallo, 2019).

6.1.1.6. Acquire

How leaders strike a balance between acquiring needed talent and retraining existing talent to fit the data culture is a necessary step in building a foundation of knowledge to facilitate data behavior. Not all employees need to become data scientists but data literacy should be improved across the entire organization (McAfee & Brynjolfsson, 2012; Ross et al., 2013; Ariker et al., 2014; Schein, 2016; Mayhew et al., 2016; McKinsey & Company, 2016; Watson, 2016; Chin et al., 2017; Gourévitch et al., 2017; Hazan, 2017; Diaz et al., 2018; Qlick & Accenture, 2020).

6.2. Framework Development

6.2.1. Table 7: Development Document

Concept	Examples(s)	Authors	Actions Origins
Attention *Definition: What leaders pay attention to on a consistent basis* (Schein, 2016)	*"(...) there must be an ongoing, informed conversation with top decision makers and those who lead data initiatives throughout the organization."* Díaz et al., 2018, p. 4	McAfee & Brynjolfsson, 2012; Mayhew et al., 2016; Schein, 2016; Watson, 2016; Díaz et al., 2018; Bague et al., 2020; Qlik and Accenture, 2020	**Action 1:** McAfee & Brynjolfsson 2012; Mayhew et al., 2016; Watson, 2016 **Action 2:** Diaz et al., 2018 **Action 3:** Diaz et al., 2018; Bague et al., 2020;
Allocation *Definition: How leaders allocate resources to projects and initiatives* (Schein, 2016)	*"(...) but also how their managers support investments and operations related to analytics."* Thirathon et al., 2017, p. 777	Carnall, 2007; Brown et al., 2013; Schein, 2016; Chin et al., 2017; Thirathon et al., 2017	**Action 1:** Brown et al., 2013; Chin et al., 2017; Thirathon, 2017 **Action 2:** Chin et al., 2017; DeLallo, 2019 **Action 3:** Carnall, 2007; Brown et al., 2013; Chin et al., 2017
Acknowledge *Definition: How leaders rewards systematically* (Schein, 2016)	*"Perhaps the best way to teach people how to use data to create business benefits is to provide them with data about their own performance."* Ross et al., 2013	Carnall, 2007; McAfee & Brynjolfsson, 2012; Ross et al., 2013; Franco-Santos & Gomez-Mejia, 2015; Dhawan, 2016; Schein, 2016; Bowcott, 2017; Treder, 2019	**Action 1:** Carnall 2007; Franco-Santos & Gomez-Mejia, 2015; Dhawan, 2016; Bowcott, 2017 **Action 2:** Gourévitch et al., 2017; Chin et al., 2017 **Action 3:** Ross et al., 2013
Anxiety *Definition: How leaders react and behave through crisis times* (Schein, 2016)	*"People want to get over a crisis and challenge as fast as possible. The leader must address the size, scope and give perspective of the problem. Demonstrate control of the problem."* Baldoni, 2011	Carnall, 2007; Baldoni, 2011; Schein, 2016; Bhatia, 2017; Gillaspie, 2018; Schiefelbein, 2017; Bague et al., 2020; Nichols et al., 2020	**Action 1:** Baldoni, 2011; Schiefelbein, 2017; Nichols et al., 2020 **Action 2:** Loder, 2014; Henley, 2018; McKinsey, 2020 **Action 3:** Nichols et al., 2020
Act *Definition: How leaders display visible behavior and deliver informal messages* (Schein, 2016)	*"(...) few things are more powerful for changing a decision-making culture than seeing a senior executive concede when data have disproved a hunch."* McAfee & Brynjolfsson 2012, p. 68	McAfee & Brynjolfsson, 2012; Mayhew et al., 2016; Schein, 2016; Watson, 2016; Bowcott 2017; Hazan, 2017; Diaz et al., 2018; DeLallo, 2019	**Action 1:** Bowcott, 2017; Diaz et al., 2018; DeLallo 2019; **Action 2:** McAfee & Brynjolfsson 2012; Hazan, 2017 **Action 3:** McAfee & Brynjolfsson 2012; Mayhew et al., 2016; Watson, 2016; Bowcott 2017; DeLallo 2019
Acquire *Definition: How leaders select new members or retrain existing ones* (Schein, 2016)	*"What does is a combination: a few strategic hires (...) strategic acquisitions or partnerships (...) recruiting and reskilling current employees with quantitative backgrounds to join in-house analytics teams."* Mayhew et al., 2016, p. 11	McAfee & Brynjolfsson, 2012; Ross et al., 2013; Ariker et al., 2014; Schein, 2016; Mayhew et al., 2016; McKinsey & Company, 2016; Watson, 2016; Chin et al., 2017; Gourévitch et al., 2017; Hazan, 2017; Diaz et al., 2018; Qlik & Accenture, 2020	**Action 1:** McAfee & Brynjolfsson, 2012; McKinsey & Company, 2016; Mayhew et al. 2016; Diaz et al., 2018 **Action 2:** Diaz et al., 2018; DeLallo, 2019 **Action 3:** Watson, 2016; Chin et al., 2017; Gourévitch et al., 2017; Qlik & Accenture, 2020

Table 7 provides an overview of the development of the Framework. We include this document to be transparent about where actions origin from in literature and to exemplify how we identify and code for these actions. We have further provided a list of all used literature and their connection to embedding mechanisms. Not all authors are represented in our actions, and so the document might serve other researchers when producing new suggestions.

6.2.2. Principles & Rules

We are aware that we develop solutions to managers. We consider what this entails by setting up guiding principles and rules in our development process to ensure some level of applicability. We have been testing various solutions through sketching while asking critical questions (see Appendix 2.). Table 8 shows three general guiding principles and how we incorporate them in the framework. We showed four action rules in table 6 (see section 5.3.7.2. Reliability) we use to be consistent and aligned with guiding principles when constructing actions.

Table 8: Framework Principles

Should be	Addressed by
Easy to understand	Simple formulations
	Descriptive titles
	Color-coded characteristics
	Implications of mechanisms included
	Definitions of mechanisms included
Easy to remember	Renaming mechanisms to begin with “A”
	Name abbreviated as 6A – *instead of AAAAAA*
	Reordering mechanisms to be comfortable to say in sequence
Easy to use	Action component included in suggestions
	Separating data culture into three approachable components
	Linking mechanisms to actions and to their implications

6.3. Discussion

In this section, we test the framework against three hypothetical organizations by discussing each transition dimension in a constructed context of three typical types of organizations, made to resemble real scenarios. These hypotheticals help us identify potential weaknesses of the framework in these contexts but also allows us to understand how different organizations might utilize the framework under different sets of conditions.

6.3.1. Hypotheticals

In tables (9, 10 & 11) below we present the three hypothetical organizations, The Large-, The Government and The Small organization. The main challenge for all three hypotheticals is the lack of data culture and each of the organizations strive towards becoming more data driven by applying the 6A framework.

Table 9: Hypothetical #1 – The Large Organization

Attribute	**Condition(s)**
Company Size	10000
Financial Resources	Strong
Risk Tolerance	Medium. High willingness to invest but would rather invest safely than take large chances with huge potentials. Slightly reluctant to experimenting
Bureaucracy	Medium. Many decision-makers but overruled by the executive team. Mid-level managers have decision-making authority but big decisions needs approval
Management Characteristics	Impersonal. “Hunch based” decision-making, based on shared experience. Aging C-suite level, focus on traditional practices proven to work, reluctant to change, results-driven, large distance between C-suite level and lower-level employees
Data Capabilities	Medium: Strong technological infrastructure, strong analytics department but weak data literacy outside of it, have opted for the “obvious” data capabilities, difficulty translating data insights to business intelligence, it is not clear who hold what skills
Flexibility	Medium. Semi flexible for adapting to change or changing environments, can be difficult to change underlying infrastructural elements due to company size
Stability	High. Low replacement in management, strong industry presence for decades, stabile culture, employee job-security (low anxiety)

Description
The Large Organization is an industry leader in a traditional industry, established in the early 20th century. What originated as a family business was later bought and merged with several other promising companies and employs 10000 people as of today. The company is now looking to make its data initiatives more efficient.

Table 10: Hypothetical #2 – The Government Organization	
Attribute	**Condition(s)**
Company Size	250
Financial Resources	Moderate. Financed by the government
Risk Tolerance	Low. There need to be strong arguments for a return of investment, investment areas are decided prior to scanning for opportunities, strict criteria for investment and often as a part of a larger overhauling of several government-owned organizations
Bureaucracy	High. Big decisions are often made outside of the organization - i.e. by politicians, high levels of governance, any change or decision must be approved by top-management inside the organization and often by several different people at different levels, management are too being managed by higher government instances
Management Characteristics	Humanistic. Employees well-being is a prioritization, process oriented, making decisions to satisfy a bigger agenda and not based on a profit-driven standpoint
Data Capabilities	Medium: Potential for huge amounts of data across different government owned organizations, however general low data literacy and limited technology infrastructure, systems are built to be used by many different organizations instead of catering to individual organizational needs,
Flexibility	Low. Difficulty changing processes, most processes are governed by checklists or specific steps, organizational change occur slowly and often due to change in government officials or lawmaking
Stability	High. Low replacement rate in employees (low anxiety), medium replacement rate in management. Generally stable culture due to a culture deriving from being government-owned which overrules the replacement in management, employee stability is reflected in financial benefits such as pensions
Description	
The Government Organization originated as a government initiative in the mid 90s, created to help and provide consultation to start-ups and entrepreneurs. The company is run by government funding and has become aware of the use of resources inefficiently. It has been suggested outside of the organization that data analytics might produce insights to help resource allocation.	

Table 11: Hypothetical #3 – The Small Organization	
Attribute	**Condition(s)**
Company Size	25
Financial Resources	Weak
Risk Tolerance	High. Always looking for new opportunities but is limited by financial resources, constantly looking to gain competitive advantage to secure strategic position in market
Bureaucracy	Low. Few decision-makers, high chance of project-approval, rules are not as developed and governed yet, lack of responsibility delegation causes less friction
Management Characteristics	Humanistic. Small distance between C-suite level and lower-level employees, "hunch" based decision making, based on missing experience. Blurred roles, overlap in responsibility
Data Capabilities	Weak. close to non-existent. Basic data initiatives such as google analytics, human data capital is spread across functions, it is not clear who can do what, difficulty generating data insights
Flexibility	High. Extremely flexible, change can occur almost over-night
Stability	Low. High replacements rates in employees and management, unstable culture, employee job-uncertainty (high anxiety)
Description	
The Small Organization has existed for 8 years and was founded on an innovative product idea. Great products have since been the primary factor for early success and has led the company to grow from 2 founders to employ 50 people. However, competition has risen on market and the company is now looking to use data analytics to gain competitive advantages.	

6.3.2. Mechanisms

The first part of the discussion will seek to answer: How effective is the 6A framework to different types of organizations? We highlight the most relevant hypothetical conditions to each of the six tools and include suited points we find interesting. The second part of the discussion will reflect upon the relation between the tools and briefly reflect upon macro- and subcultures, which has not been accounted for in the 6A framework.

6.3.2.1. Attention

As apparent from literature, several authors focus on the importance of commitment from top management and stress that "(...) commitment must be manifested by more than occasional high-level pronouncements" (Diaz et al., 2018, p. 4). Consistency in what leaders pay attention to is key when considering Attention. Attention could be establishing ongoing conversations where focus should be on listening and sharing data-oriented feedback. However, we acknowledge that establishing ongoing conversations, systematically asking data related questions or using tools consistently is not done through a 'one fits all' approach. Instead, how attention is displayed and expressed appropriately is dependent on the type of organization it is applied to.

The Small Organization will naturally be able to apply Attention consistently when asking data related questions and maintaining ongoing conversations between relevant decision-makers in the organization. Due to smaller teams, fewer decision-makers and limited tools, using Attention for leaders seems to be practical, as it will most likely be much easier to be consistent with Attention if there are fewer things to pay Attention to. In general, The Small Organization is very flexible and can change and adapt as it gets new insights, which is why a fail and learn fast characteristic is quick for a small company to obtain. However, there is also a tendency in this organization of higher replacement rates in both employees and management, which can compromise attentive focus for especially two reasons; first, when there is a high replacement rate in employees, managers need to constantly guide and integrate new employees in how to work with data to ensure that new employees are 'on board'. Being consistent with

Attention might be an issue with sudden distractions caused by replacements. Second, when there is a high replacement rate in management, it creates real difficulties, as a new manager must first realize the benefit of using Attention as a cultural tool for it to be of any value. We believe the same can be said about the other five mechanisms, but it is an issue mostly related to companies with frequent changes in management and workforce.

The Government Organization is a middle-sized company and they will share some of the benefits of being a smaller company in terms of consistency. However, the immediate issue in this organization is a high level of bureaucracy. Decision-makers are less visible and big decisions are made outside of the organization. Nonetheless, any change or decision must be approved by top management, and sometimes government officials on the outside, as well as go through several people at different levels on the inside. This means that ensuring alignment throughout the different units is difficult, not only because every update must reach the right manager but also because appropriate data questions and feedback must be produced and communicated back through these different levels. As a result, bureaucracy makes a fail fast characteristic more difficult to develop for this organization. We wonder, since each initiative is at least partially financed by the government, if failure might not be as welcome in this organization.

The Government Organization has, however, great potential to access large amounts of data when living in a government ecosystem with many partners and supporting organizations. But in order to become successful with data analytics, it is important to realize that the data itself is not the most important factor, but rather that the leader is able to clearly and consistently communicate that analytics is expected to be part of any decision-making process (Watson, 2016, p. 7), foster collaboration and insist that insights are used (Mayhew et al. 2016, p. 13). We talk about the little value big data has as a resource by itself in a previous section (see section 2.1.), but it becomes clear in a company such as The Government Organization, that access to data alone is not worth much if managers below C-Level have no to little control of how it is used. There is an argument to be made here; if leaders below C-level experience high friction when trying to influence processes, or have restricted control of data resources, being consistent in Attention delegation becomes almost impossible.

The Large Organization will too experience much difficulty ensuring consistency throughout the organization, but mainly due to its many members and scattered units. It will be challenging to make sure that every employee is heard and provided with feedback. Also, demanding managers to ask data-related questions in continuous conversations with many different stakeholders does not seem efficient in practice. However, a strong strategic position in different markets and financial resources enables them to provide appropriate training to managers and qualify them to ask data-questions and engage in data conversations. We consider this to be of important value. If a manager is looking for something specific in an answer, the manager must also learn to construct relevant and fruitful questions.

The Large Organization has a strong technological infrastructure and analytics department. But due to the otherwise low data literacy outside of the department, not every member of the organization can be asked data questions or answer insightfully. We read about similar real world scenarios in our research, where organizations have undergone huge technological transformations and are set up to do advanced analytics but find it difficult to translate data insights throughout the organization because people outside of the analytics department do not seem to speak the same language or value the same things. In these cases, it might be even more important for top managers to be aware of what they pay attention to and set clear expectations for everyone in the organization. This also includes paying attention to which tools are used across the organization and how they can be used more consistently. In general, technological infrastructure tends to be complex in large companies with many systems and tools in place and as a result, developing common language through Attention is more complicated. On a side note, it seems to be culturally beneficial if less systems and process tools are used.

Most organizations today do acknowledge that it is critical to be able to rapidly review, react and adjust to real-world results (Ariker et al. 2014) and part of that is having data conversations on a continuous basis with the right people involved. Managers will have to be up to date with the utilization of company data and be able to identify key questions to ask (Mayhew et al. 2016). We argue that the Attention mechanism in the framework is accessible to each of the three hypotheticals, but a larger number of employees and systems in place adds to the complexity of being consistent, bureaucracy conflicts with establishing ongoing conversations with top decision-makers and a high replacement rate can cause distractions when delegating Attention.

6.3.2.2. Allocation

We advocate for the importance of budgeting for data analytics. Not just for obvious investment related reasons, but because prioritizing specific activities within a budget sends a clear message to everyone in the organization. It is a way for leaders to communicate what the important financial activities and tasks are for everyone to focus on, in order to maintain broader strategic goals (Thirathon, 2017). This is when it becomes a tool for culture transition (Schein, 2016).

A core theme when we talk about Allocation is a company's ability to support initiatives financially and The Large Organization will have a natural advantage of size. The company is strong, established and with financial strength comes the ability to invest more diversely and to Allocate towards many initiatives. There might be power in employees being able to say, "we launch many different data driven projects at The Large Organization". It also seems to be the only hypothetical organization with enough financial strength to be able to budget for failures. Considering that many efforts will fail is an important component (Chin et al., 2017) when developing a fail and learn fast characteristic and The Large Organization is particularly suited for doing so.

Contrary, The Small Organization will have to be much more thoughtful in picking the right projects, as its financial strength is weak which means resources are scarcer. However, at the same time the company is more willing to take risks. This can be a powerful trait when we consider it in a culture context. We wonder what kind of message it sends throughout the organization, if leaders are willing to Allocate a large portion of the budget on a few data driven projects. It could be that such a message resonates even more in The Small Organization as these big investment decisions communicate a strong belief in data projects, with more at stake should they fail.

Allocation in The Government Organization is subject to other constraints. Government companies typically employ short-term budgets which is reflected in their ability to prioritize innovation. In our hypothetical, the organization possesses moderate financial strength and would most likely be able to allocate appropriate resources, however facing restrictions in other areas, such as getting allocation approved or acknowledged by leaders higher up in the organizational hierarchy. Allocation is driven and must be supported by many individuals with different interests. This form of bureaucracy could be negative for the company when undergoing a culture transition, as it sends mixed financial signals to its employees. There might be leaders present at times believing strongly in experimentation and data analytics, but with a longer chain of command, short-term budgets and a slower investment prioritization process, expanding outside of the company, the message of leaders believing in new data projects by allocating resources to the cause might not even come across to its employees. As the company's policies and business strategy is influenced by a larger governmental agenda, Allocation could be difficult to utilize in The Government Organization. In addition, the purpose of government organizations tends to be less profit-driven, as opposed to the other two hypothetical types. This raises another question; will the company then see less value in budgeting for data analytics related projects, as one goal of big data investments is to generate revenue through process optimization? (Wamba et al., 2014, p. 24).

The opposite is true for The Large Organization, where middle managers have decision-making authority and bureaucracy causes less friction. It is then possible for leaders of various business units to affect budgeting in a data direction. But utilizing budgeting in a culture transition includes more than just setting aside financial resources for projects. There are multiple ways for a company to send a strong financial message to its employees. If leaders are to be evangelists for change, they themselves need to change and acquire new knowledge (Hazan, 2017, p. 4). This requires them to undergo some form of training to ensure they possess the skills necessary (Carnall, 2007, p. 43). Hazan (2017, p. 5) and Brown et al. (2013, p. 3) suggest that leaders should visit organizations where data is already boosting performance significantly to learn from it and get inspiration. While the cultural implication is the same as budgeting for projects, organizations should Allocate for education of leaders and members. It has communicative value that the organization prioritizes to train a leader of a business unit in data analytics despite the fact that the leader will not be able to manage employees and perform critical tasks while undergoing training. The same mechanism is at play when we consider educating the workforce. It sends a clear message throughout the organization that a company is willing to spend money and time, temporarily removing employees from their respective functions to strengthen analytical skills and improving data literacy. But the size of the organization might influence the company's ability to execute such action in various ways.

There are not that many leaders and employees to train in The Small Organization. However, the company is especially vulnerable to members missing workdays and not performing assigned functions, as the organization does not have the human capital required to temporarily change functional areas and keep them running by using other members with overlapping expertise. In addition, the company might have to prioritize budgeting for training over projects first, as its existing human data capabilities are very limited. On the contrary, The Large Organization will face other challenges. They can budget for both experimentation, failures and training, but training thousands of members will have to happen in stages and on different levels. It seems that the big challenge in this case is more related to coordination. Brown, Court & Willmott (2013) claims that large companies are often surprised by the arduous management effort involved in mobilizing human resources across many business units. The Government Organization will have it easier when coordinating and maintaining functional areas while training due to its size, but the specifics of the training could be difficult to determine as not all data capabilities are obvious to the organization itself and short-term budgeting can hinder its ability to train all members. This then becomes a question of prioritization – what to train for and how to do so.

6.3.2.3. Acknowledge

As apparent from the framework, we draw attention to the importance of rewarding employees. Employees are more motivated and willing to go the extra mile to complete important tasks when they are acknowledged for doing so (Franco-Santos & Gomez-Meja, 2015, p. 2). It is through reward systems that leaders can define what is being valued as important for the organization to each individual as well as an expression for defining what success looks like in the organization (McAfee & Brynjolfsson, 2012).

An established company, like The Large Organization, will have a good foundation to Acknowledge members extrinsically, for example through compensation, promotion or other benefits. But we note the importance of rewarding at every level of the organization, and how does a large company monitor all employees at every level of the organization and determine success across many different disciplines and functions? Also, considering how expensive it would be to reward continuously. Even though we set a financially strong condition for The Large Organization, the term does not stretch infinitely. The company will have to consider in which areas it particularly wants to reward for data behavior and how it should be done. In this case, size makes it more difficult to Acknowledge all members of an organization. In addition, large companies tend to be more impersonal with long distance from C-Level to front desk workers. Rewarding intrinsically might be even more difficult, if members at all levels are to feel significant to an extent where they think of quality and excellence as something worth striving for (Carnall, 2007).

Issues related to the Acknowledge mechanism seems to be caused by structure rather than size in The Government Organization. Rewarding at different levels is more achievable but we imagine that this company does not have the freedom required to reward extrinsically, as its fixed short-term budgets and government funding structure is not flexible enough to accommodate for sudden monetary acknowledgement. Furthermore, Carnall (2007, p. 151) argues that paying attention to the timing is crucial and the leader must ensure and reward the very early success in order to cultivate employees from the beginning. If The Government Organization is to Acknowledge early success, rewarding intrinsically should be considered. It might be that the humanistic values in management provide leaders with a better understanding of employee relationships, making intrinsic rewarding even more effective.

The Small Organization is also challenged in its ability to reward extrinsically, but due to lacking the financial resources necessary. However, The Small Organization is well positioned to reward intrinsically as relationships are more personal within the company. They are also more likely to identify the right timing for rewarding due to smaller teams and better overview of all projects. The leader has the advantage of being able to clearly recognize what type of intrinsic acknowledgement is appropriate for the individual employee. For example, should the leader provide the employee with a sense of meaningfulness by acknowledging the significance and purpose of the work? Or perhaps provide a sense of growth in which the employee feels confident for performing the required work skillfully (Franco-Santos & Gomez-Meja, 2015). It can be argued that it would not be beneficial for this organization to set up specific reward systems, as changes in this company occur almost overnight and such systems are too inflexible for a chaotic environment. Instead, leaders must exploit their ability to adapt and reward as soon as desired behavior is identified.

Alongside rewarding at every level, ideally in combination of both intrinsic- and extrinsic acknowledgement, an organization should provide employees with data about their own performance. Doing this does not only allow the individual employee to understand how their activities contribute to the overall business success or how they can improve and get a sense of what they are doing well (Ross et al. 2013, p. 1). It also illustrates that the organization chooses to apply data when measuring performance. It can further help to stabilize the organization by guiding employees in the direction laid out by the company, if they are provided with specific instructions of how to get there (Schein, 2016).

The Large Organization would be able to apply scorecards to clarify individual accountability due to its strong analytics department. However, the company finds it difficult to translate data insights, implying that even though employees can be provided with data about their own performance, it might not be possible to provide them with a further explanation, justification or perhaps guidance to justify new actions to take. This is problematic as the most important objective of scorecards must be to offer results that the individual can control. It first becomes a cultural tool at that point. It is crucial that the purpose of the scorecards is to create a friendly environment in which the employees can use it as a motivating tool to see how much they have improved (Ross et al., 2013, p. 3). We recognize the logistic issue of providing scorecards to thousands of employees. Instead, The Large Organization could measure and produce scorecards for key positions in functional areas to accommodate.

But the number of employees and data capabilities are not the only limiting factors when considering scorecards as a cultural action. This is one of the many instances where The Government Organization is in a middle position to take advantage of a mechanism. It would seem that the company is able to gather the needed data, or at least take advantage of its many partners to understand what is required to gather performance data on employees. In addition, with relatively few people in the organization and more visible humanistic values in leadership, measuring on all levels is achievable. But inflexibility in general structure causes implementation across departments to be difficult. We mention that tools must become of universal use in an organization to develop common language. This action is only effective if all managers and leaders in the organization are in agreement of its use.

The Small Organization, on the other hand, has an advantage as it does not have to be selective when choosing who to produce individual scorecards for. The pressing issue for this company seems to be its limited technological capabilities. We wonder how advanced capabilities should be, if a company is to produce insightful suggestions for members to take based on work performance. It could be interesting to monitor what it means for a small company's overall business performance if every employee is provided with unique scorecards. It might mean that the overall performance would increase and become more effective as it is possible for the individual employee to detect and react to problems before they affect the business on a higher level (Ross et al., 2013).

6.3.2.4. Anxiety

When we talk about crisis response, we do not mean how an organization can prevail through a crisis with proper crisis management. However, we do offer specific actions for leaders to follow while navigating through turbulent times. People want to get over a crisis as fast as possible. The leader must address the size, scope and give perspective of the problem and demonstrate control (Bhatia, 2017; Baldoni, 2011; Carnall, 2007). According to Schein (2016), anxiety levels are heightened during a crisis, and the need to reduce anxiety is a powerful motivator for new learning. People in the organization are more likely to repeat behavior that has proved to reduce anxiety if they have shared intense emotional experiences and collectively learned how to behave during such experiences. This means that leaders who manage to implement or prove the effectiveness of data based solutions under a crisis is able to contribute significantly to the transition towards a data culture.

Crises come in very different forms with varying implications. Some threaten the office atmosphere in a department while others are threatening the very existence of a company. In other words, crises can arise on different levels, both externally and internally, and is a crisis if the leader views it as such (Schein, 2016). An effective leader must find ways to engage and motivate, clearly and thoroughly communicate important new goals and information (Nichols, Hayden & Trendler, 2020, p. 4). In our three hypothetical organizations, it is most likely the case that they each undergo crises of very different nature – not considering global ones like the stock market crash in 2008.

The Large Organization will, due to its size, scattered activities and divided focus, be susceptible to more threats across its various business units and functional areas. But it also provides opportunity for leaders to instill data driven behavior into these units. It might be that the marketing department falls short in understanding the target group for a new product, causing a threat to the success of the launch campaign, or that the financial unit has been archiving inconsistently and is now having difficulty locating mistakes in necessary financial statements. It is in situations like these that leaders may transform espoused beliefs about data into underlying taken-for-granted assumptions, if they manage to dissolve the situation and reduce anxiety in the workforce with data solutions. It could be that the marketing department finds success with new data collection processes and analytical models or that the financial unit reorganizes its database with new software able to categorize and monitor all entries.

On the contrary, The Small Organization is much more focused in its activities and so is The Government Organization. But their employees are also susceptible to anxiety. In this data culture context, we are stressing that a crisis might simply mean anytime something causes a rise in anxiety on a group level. And if a leader can reduce this anxiety through a data solution, the group has collectively been convinced about the use of a new process. This is when reducing anxiety becomes a culture tool and why we define it Anxiety.

General for the three hypotheticals is that all anxiety induced situations cannot be solved with data initiatives. It is unclear how often crises occur in real companies, similar or different to these hypotheticals. But if a situation can be solved using big data ideas, in any form, it is a powerful message to inject into a unit or a whole organization committing to a culture transition.

What really sets the hypothetical organizations apart, however, are the reasons for induced anxiety – or types of crises they are likely to face. It is difficult to imagine very specific situations in each of them and it might not be valuable to be too reductionistic. Situations causing anxiety can be anchored in factors unique to each company such as industry, location, strategy and so forth. Instead we will discuss the conditions of the organizations we believe to be most influential to the effectiveness of the Anxiety mechanism.

A condition of The Government Organization is its overall rigid structure with low flexibility, lacking the speed and ability to respond immediately. However, the organization does have an overall stable backbone with established processes ingrained into it. Stability further offers comfort and reduces anxiety (Schein, 2016). This implies that even though The Government Organization lacks agility, it can utilize its stability as a strength in times of crisis. Government owned organizations have even been recognized as doing better under a crisis, compared to how it usually performs (Dowdy, Rieckhoff & Maxwell, 2017). This type of company is able to provide a clear vision and direction and the organization's structure naturally defines the distribution of people and resources very clearly. Top management, also outside of the company, determines how things will be done and commands they are done that way. This means that the organization has controlled levels of anxiety due to its stable structure, its low employee replacement rates, governmental support etc. In such instances, the comfort of 'being backed by the system' (whether it is actually true or not) and its rules, regulations and managerial structure could naturally lower the anxiety in the organization when facing a new crisis. At the same time, we wonder if this makes the Anxiety mechanism less effective, as reducing anxiety does not have the same immediate cultural effect in this company.

On the contrary, The Small Organization experiences high anxiety because of uncertain circumstances and a chaotic environment. The organization is very flexible and capable of adopting new solutions fast, although limited data capabilities also restrict its ability to use complicated data solutions. Nonetheless, the impact of the Anxiety mechanism seems more potent and visible in comparison to The Government Organization. This is not to say that every organization should not look to use culture embedding mechanisms in anxiety inducing situations, but it will be more accessible to some.

So far, we have discussed each hypothetical case as if they were facing threats only relevant to themselves. But in section 2, we describe how all companies need to be data driven or they could lose their industry position and become unsustainable in the long run. In this context, organizations all over the world are facing a global crisis – become data driven or die. In a crisis, according to Schiefelbein (2017, p. 3), the combination of what leaders say, how leaders say it and the actions that follows will determine how the organizational image is remembered. It seems to be the perfect opportunity to articulate a strong change story and take advantage of the unavoidable crisis.

6.2.2.5. Act

Leaders in companies are naturally in positions where their actions and sayings have strong influence on the people they manage, and it reflects directly on the organization they represent. This is one of the main reasons why leaders are so important in culture transitions. How leaders, especially top managers, behave in front of employees and what they say they believe in is transmitted to employee behavior.

First, it is important to articulate a strong change story. This story should be formulated at C-Level and aligned throughout the entire organization to foster the conviction that transformation is right (Bowcott, 2017, p. 6). It also includes articulating what is expected of the employees (Watson, 2016; Qlik and Accenture, 2020). It must be noted that a change story is unique to the company and a part of its most visible culture. We do not know much of how a data culture change story is best articulated but we imagine it needs to be tailored to current circumstances, meaning it should be relevant and powerful in addressing current challenges while providing at least the belief that being data driven is a crucial part of the solution.

Aligning and convincing an entire company will be more difficult in The Large Organization with its many employees and leaders. Here, the change story will be restated at every level of the command chain. It could be hard to ensure that the story remains as strong as intended, so that no business units are less convinced or 'onboard'. This is one example where middle management plays an important role. According to Takehiko Nagumo, executive officer at MURC, middle management justify ideas from upper management and implement them throughout the organization (as cited in Diaz et al., 2018, p. 11). In a cultural context, the role of middle managers becomes to align the different subcultures of functional areas with the greater organizational culture. For this reason, the 6A framework does not just concern top management but can be used by every leader at every level within the company.

The situation is more unique in The Government Organization. Due to its structure and place in a government ecosystem, the chain of command extends beyond company barriers and into other organizations and units. Here, the change story might be formulated far away from the company, and we assume this makes implementation difficult. But on the other hand, the government ecosystem is heavily influenced by changes in the political climate. Companies operating in such an ecosystem might be used to communicate high-level change stories ever so often, whenever a new story or law is articulated by a government.

Another defining part of role modeling is the visible and audible behavior a leader publicly displays, as mentioned in the beginning of this section. McAfee & Brynjolfsson claims that “few things are more powerful for changing a decision-making culture than seeing a senior executive concede when data have disproved a hunch” (2012, p. 66). In addition, Bowcott (2017) states that visible role modeling in culture transition is among the most important force multipliers. Also, DeLallo has expressed it quite simply: “when workers *see* the executive team making data based decisions, it becomes easy for that kind of decision-making to flow through the organization [and] when workers *hear* the executive team talking about making decisions in that way, they say, “of course they’re going to expect me to make decisions in a similar way” (2019, p. 2). These statements stress why the Act mechanism is so important.

We find that size often changes how the mechanisms we provide are implemented, prioritized or the effects of them. However, here is where role modeling might overcome some of the restrictions that comes with this condition. It would be an easy position to take, that The Large Organization will find it more challenging to manage visible role modeling for all its leaders. And this is likely accurate, if it were not for the true power of this action. Considering the history of business, many great CEOs have done Acting so well that it even changed customer behavior. This is a common narrative among top global performers. Apple and Steve Jobs is a quick mention, though many others could just have been. In this context, Jobs did particularly well at product launches, and it is in situations like these, that the Act mechanism becomes very capable. The product launches, showcasing Jobs interacting with the latest technology innovation and talking about his assumptions, viewed by millions online, are great examples of behavior so visible that it has an effect all the way throughout the culture in a huge company. In other words, every leader in every organization should understand how their visible and audible behavior can be used to steer an organization through a culture transition.

On an additional note, it might be difficult for top management with reluctance to change to become good role models. In The Large Organization, conditions like aging management and low replacement rate at C-Level can become problematic if not addressed in time. The possibility of failure is high when companies do not commit leadership (Brown, 2013) and we come across similar statements in literature often. Leaders in The Large Organization are much less visible to all employees, in comparison to The Small Organization, but we can imagine how difficult it will be to convince leaders at lower levels of cultural change, if top management does not take a strong position from the very beginning. But at the same time, leaders of large companies will have better conditions to approach role modeling strategically than leaders of small ones.

On a further note, it is not clear to us who the role models are outside of The Government Organization. There are likely leaders in different places of the ecosystem who are entirely invisible to the employees of the company. In this case, we question if top management is even able to commit to change, if leaders outside of the company do not – or is not even identifiable.

6.2.2.6. Acquire

Assembling a great team can be difficult (Mayhew et al., 2016) as it requires the leader to carefully consider the appropriate balance between transforming existing employees and hiring new talents (Diaz et al., 2016). We create awareness on the talents needed for building a data culture. By establishing the right balance between recruiting and reskilling, the leader builds a sustainable foundation of data knowledge in the organization. This is important for many reasons but specially to build common language and skill across the company.

It will be challenging for The Large Organization to determine the right balance between critical data capabilities needed and what is already covered by its large workforce. Mayhew et. al (2016) states that "simply throwing money at the problem by paying a premium for a cadre of new employees typically doesn't work" (p.11). With the company's strong analytics department but otherwise low data literacy in the rest of the organization, we imply that The Large Organization has done exactly that in an attempt to cover its data capabilities. Instead, the combination between hiring new people and training existing employees is argued to be the key to succeed with the Acquire mechanism. But committing to extensive retraining of the entire organization is also a matter managing the risks involved. In this light, the low replacement rate in The Large Organization (relative to its size) will benefit the company and make it a more attractive choice to educate and create confidence in employees when working with data analytics (Qlick & Accenture, 2020, 11) as they are more likely to stay in the organization for longer periods of time.

The same is true for The Government Organization, where low employee replacement rate allows them to maintain talent within the organization for longer. But it will be difficult for this company to strike an appropriate balance of the two disciplines, as they have little knowledge of where talented individuals are located – most likely because they were recruited with different functions in mind, and also no way of tracking individual unit performance to determine weak points in the organization. The point we make here is that the Acquire mechanism is hard to use in practice if a company is not able assess current capabilities prior to using the mechanism.
Contrary, The Small Organization will have an advantage as talent in the workforce is more visible and accessible to the leader. With fewer people to assess and more interpersonal relationships, the company can effectively determine who possess what skills, what skills should be taught to existing employees and what talent the organization needs to recruit. This is one of the reasons why small companies are so effective in building common language. However, the company will be challenged on its financial resources in terms of the costs associated with training or hiring new people and getting them acquainted in the data culture. The advantage of size could also be challenged on replacement rate. With high replacement in both employees and management, the company will have to determine its needs on a continuous basis as well as spending resources for reskilling and re-hiring new employees, so it once again can assemble a great combination of skill with ability to navigate
in a data culture.

The Acquire mechanism is probably the one with most immediate effect on developing a common language. One of the primary outputs of putting employees through data analytics training is increased vocabulary and ability to speak about data and understand when data is spoken of, thus directly building language. But building language with many people involved is difficult and The Large Organization will be challenged when improving data literacy across the entire organization (Qlick & Accenture, 2020). However, note that the large company, AT&T, have managed to offer 50.000 data courses to employees in one year alone (Victor Nilson, found in Buluswar et al., 2016, p. 5). This speaks to not only how important it is for leaders to train and build common language but the possibility of acquiring talent on a large scale. Also, we do not see how large companies with thousands of employees can ever maximize its use of analytics, if there are areas within organization where the common language is not spoken. We mention, when talking about allocation (section 6.2.2.2.), how training would likely happen in stages over time in a large company.

We have circled this condition several times when talking about The Government Organization; but its potential to access data from government partners and other companies in the ecosystem remains a strong quality if taken advantage of, especially in a company that struggles to allocate for the Acquire mechanism. We envision that the organization can accommodate for this, to a degree, if they decide to insource parts of the training. With a lot of data available, simple initiatives could be put in place with the objective of building fundamentals of a common language, for example through democratization of the data.

In the framework, we also suggest leaders to 'teach people to fail and learn fast' under the Acquire mechanism. We do so because a company must acquire this characteristic to make most use of data analytics – on the same level as building language and making decisions based on data. It is immediately more difficult to see how a company can train to fail and learn fast. We can think of training decision-makers to be able to close projects based on data and be able to analyze and identify key learnings from the failure to communicate to other projects. We see no reason why The Large- and Government

Organization would not be able to follow this suggestion, if the involved training was more approachable and obvious. However, in The Small Organization, such skills can be acquired naturally from the many failing efforts that most small companies endure when building and scaling.

6.3.3. Relations

The 6A framework demonstrates that a leader can not simply throw money after expensive data initiatives or hire a lot of talents and through that succeed with data analytics (Mayhew et al., 2016). Instead, the framework proves that the leader must use several mechanisms continuously as they are interconnected. If the leader reaches the understanding that the mechanisms are related, it will benefit the work that is put into transitioning into a data culture, as the leader will be more effective when combining or identifying overlaps between mechanisms.

We identify Allocation to be a very central component of the framework. When discussing several of the other components from the framework in relation to the three hypotheticals, it becomes clear that they often depend on financial resources. This could be exemplified with the Acquire mechanism, where it becomes apparent that this dimension is highly dependent on considering the availability of allocation of resources, as acquiring new talents or reskilling existing employees is partly a financial matter. The same applies to the Acknowledge mechanism, as rewarding employees, particularly extrinsically such as through promotion or salary compensation (Franco-Santos & Gomez-Mejia, 2015, p. 4-10) requires a certain level of financial resources being allocated into that action. In fact, it does not make sense, nor is it possible at all, to consider rewarding employees extrinsically without considering the resources of an organization. This is an attribute that clearly differentiates the three hypotheticals as they each are in very different financial situations. Furthermore, we identify Allocation to be very significant when discussing the Act mechanism. If a leader is expected to act as a role model for employees in order to encourage change, the leader needs to acquire new knowledge in the area they want to see change (Hazan, 2017). This often means that leaders must undergo training to achieve the necessary knowledge and skills

(Carnall, 2007). Therefore, it would not make sense to consider the Act mechanism without accounting for the costs of prioritizing such training. Conclusively, we find that without assessing company resources, it is difficult to make a realistic depiction of implementing the other components and we therefore recognize allocation as being a very central mechanism, as it enables several other mechanisms to function.

Another mechanism we often consider when working with any other mechanisms is Attention. Attention consistency is a dominant component to consider, in example when determining the right balance between hiring and reskilling, as suggested by the Acquire mechanism. Identifying what is sufficient and what is lacking in the organization can be very difficult without asking data related questions, having on-going conversation and assessing current big data tools. The leader must through ongoing conversations identify and establish what the organization is missing to reach strategic goals and understand what knowledge and skills the organization currently holds. We also find Attention to be important in terms of rewarding the employees, especially when considering intrinsic reward systems. Rewarding with a sense of meaningfulness to make employees feel significant does not make sense without paying Attention to what the employee actually did great. This matter is further addressed by Franco-Santos & Gomez-Mejia who argues that "compensation and benefits alone are no longer effective as motivating mechanisms because they cannot create the employee engagement required to compete in today's complex and fast-moving business environment" (2015, p. 11). Instead, a combination of extrinsic and intrinsic rewards are necessary and in order to establish what type of reward is appropriate for the individual employee. It must carefully be appointed by gathering an understanding of the employee's performance as well as values, which can only be done through attentiveness. Generally, we find that in order for a leader to drive, encourage and demand change in the organization, it is important that the leader is attentive, not only in regard to the three actions suggested under the Attention mechanism, but to each of the six mechanisms.

We have established and accounted for the importance of leaders in culture transition throughout the paper. One of the most visible reasons for this is because of the Act mechanism. To be a good role model is essential and why we see this mechanism reflected in many of the others. For example, when handling and navigating through turbulent times, the leader is required to demonstrate control (Bhatia, 2017; Baldoni, 2011; Carnall, 2007) as well as clearly and thoroughly communicate important new goals and information (Nichols et al., 2020, p. 4), which implies that it is expected that the leader take on a specific role for, in this case, reducing anxiety. However, it will only be of value and be conceived as a strong act, if the leader also advocates for change and visibly displays behavior in line with the desired change. Therefore, it is necessary to not only consider how a leader should act in difficult times, but also how the leader actively demonstrates control and is a good role model for advocating change in general. This will eventually prove to be even stronger and more convincing when the leader still assumes the role when difficult times occur, and the anxiety increases in the organization. Furthermore, the Act mechanism is also related to Acknowledge and Attention as rewarding with a sense of meaningfulness or asking data-related questions only will function as the strong reward mechanism it can be, if the leader evidently expresses continuous visible and audible behavior in front of the employee. Overall, it becomes evident that leaders must act as a constant depiction of the change they require and demand the employees to adapt to and strive for. Therefore, it is the case that the Act mechanism is a very critical dimension and many of the other components are either directly or indirectly linked to it.

6.3.4. Macro cultures

We do not address macro cultures in the 6A framework, however that does not mean that macro cultures do not play an important role in an organizational culture. Instead, we scope the framework to only consider immediate actions for leaders to take with impact on their organization. But it becomes obvious, when we talk about large companies such as The Large Organization, typically with operations crossing borders and sometimes even continents, that the 6A framework is limited in its ability to contextualize its general guidance. Questions arise such as; what happens when culture transition in an organization is ongoing in more countries at once? – or will the framework be equally applicable to organizations anywhere in the world?

We see leaders who are aware of multicultural groups and macro cultures of the organization as being able to use the 6A framework more dynamically. Understanding the primary macro cultures at play allows the leader to select and plan actions with a more solid foundation for implementation as they will synergize with broader cultures.

Therefore, macro cultures are something that any leader should consider when thinking about which actions are the right ones to take. They will dictate how some of the six mechanisms are used in some instances. But thinking about macro cultures does not have to be complicated. As a digestible example, we know that shaking hands is not viewed as the preferred way of formal greeting in some places in the world. It means that if an organization would include 'more visible handshaking' as an Act action, macro cultures of these places would not allow this action to produce the same value as somewhere else where this is not the case. Although we do not believe it to be expected of top managers to become experts in cultural analysis, it helps to understand that different groups of people by nation, ethnicity or occupation within the organization will share values from outside – from macro cultures, and it is possible to build shared assumptions across cultures if leaders can identify these multicultural groups and engage them through personal dialogue.

According to Schein (2016), an organizational culture is nested in broader macro cultures. In this sense, organizational culture exists within the macro culture, and we can imagine how this might make implementation of some actions difficult. In different areas across the world, different cultural rules and assumptions will apply. It could be that in some countries, failure is viewed more negatively than in others. For example, in South Korea, grades and rankings of universities are defining for the career afterwards. The same is true in Scandinavia to some extent. However, in South Korea the standardized form of exams is multiple choice tests, visibly valuing memorization as the best learning process. The situation is certainly more complex, with many assumptions and cultural elements interacting, but on a basic level, the school system in South Korea is formed by a taken-for-granted assumption in society, that you get a good life if you go to a good school and get good grades. This will reflect particularly in students' competitive habits and high level of anxiety due to pressure to perform. It means for some students that failure is not even an option.

As for our framework, what happens when a leader tries to enforce a fail-and-learn element to an organizational culture in a country where failure is overwhelmingly portrayed as bad behavior? Or when the leader puts two groups of people together who views and understands failure differently? There are mechanisms at play that leaders will have to consider. First, is it even feasible to implement a fail-and-learn element in these cases? – and if so, which other mechanisms will have to be restructured to make it possible? According to Schein (2016), we will first have to create a temporary cultural island and encourage personalized dialogue to build empathy and understanding towards other cultures in the multicultural group. But it might also be that specific tools from the 6A framework should be altered to address a macro culture. For example, specific reward systems might be set up to favor critical insights gained from failed projects, allowing employees to compete on analytical thinking and shift focus from the fact that the project itself failed. Or it could be that leaders would have to refer to failing as something else because of the negative stigma it brings, even though the word they use in replacement means the same.

It is hard to talk about macro cultural elements in The Three Organizations. We do not know enough about macro cultures in this context, but common to each of them is that their organizational culture is nested in broader macro cultures (Schein, 2016). As mentioned earlier, The Large Organization will most likely take on activities cross-border and its top managers will need to be aware of critical differences in national cultures. The Government Organization on the other hand, is most visibly exposed to another macro culture. Some members of this organization, we imagine leaders in particular, represent the government directly and are thereby a part of a broader governmental culture. We do not know the exact meaning of this in a specific company or how it extends to employees, but surely some shared assumptions are derived from being a government official. The Small Organization can afford to think less about macro cultures when utilizing the 6A framework due to its geographical scope and number of employees, but their organizational culture is also nested in broader macro cultures as with any organization.

6.3.5. Subcultures

The other main area we do not address in the 6A framework is subcultures. We have accounted for three main generic subcultures that can be observed in an organization in theory section 4.2.3., but it is not part of our scope to specify how our framework deals with them specifically. We do however know the importance of managing subcultures. Schein (2016) claims that as the organization evolves, management of subcultures becomes a primary task for leaders. This is to ensure continuous alignment throughout the organization. If we think of how this is manifested in The Large Organization, we can point to how the organization has grown to be large and spawn different departments and units as their own groups, each with their own subcultures. The same is hardly the case in The Small Organization where the subcultures only exist within the larger organization culture, as the entire organization is one group. The 6A framework is supposed to help large organizations manage their subcultures by providing the framework to managers at every level. We have previously touched on how important middle management is in these organizations, as they are the ones who validate ideas from above and implement them throughout the organization. They are the reason we specifically stress that we have built the framework on a theoretical foundation by Schein, who address leaders at all levels in an organization, so that the tools we lay on top is applicable at all levels of organizations. It is obvious how top management must become evangelists for the transition, but it might be even more important to have middle management champion the big data idea all the way down the organization. If we think about how far of a distance there is from C-level to the bottom of the hierarchy in a huge organization, providing the managers in between with culture facilitation tools seems like a necessity. How else would top management directly control cultural alignment in the entire company? In summary, we address the alignment of subcultures by providing a tool to leaders at all levels to embed a big data culture.

7. Findings & Reflections

We ask how effective the 6A framework has the potential to be in different types of organizations. We discuss this against three hypothetical companies, described to resemble generic company types. We highlight what we think to be obvious differences between them and look for main qualities and key challenges when using different 6A mechanisms. Findings Table 1 shows a collection of these points.

Findings Table 1

HE = Highly Effective E = Effective F = Friction

Hypothetical Organization	6A Framework Mechanisms					
	Attention	**Allocation**	**Acknowledge**	**Anxiety**	**Act**	**Acquire**
The Large Organization	F	HE	E	E	F	HE
Main Quality (when using the tool)	Able to provide managers with education, qualifying them to ask and talk about data	Strong financial resources allow for allocation of many initiatives and budgeting for failure	Especially able to motivate and incentivize extrinsically	Are particularly well adjusted for creating data-oriented solutions	Top leaders	Able to acquire necessary training and recruit the needed talent
Key Challenge (when using the tool)	Being consistent with many employees and decision-makers	Coordinating resources when prioritizing what to budget for and who to train	Difficulty in acknowledging employees at all levels	Susceptible to more threats due to many functional areas and units	Long distance from c-level to the lower levels makes leaders less visible	Takes much effort to create a common language across the entire organization
The Government Organization	F	E	E	F	E	E
Main Quality (when using the tool)	Potential to access a lot of data to stimulate conversations	Able to allocate appropriate resources to data initiatives if support by top leaders	More personal relationships allow for more effective and personalized intrinsic rewarding	Stable backbone i.e. clear organizational structure and operating norms	Experience in communicating change stories in an ever changing political environment	Potential to access a lot of data to build basic language and use for in-house training
Key Challenge (when using the tool)	Maintaining consistency if decisions are made outside the company	Bureaucracy slows down investment processes and weakens the message	Low flexibility causes extrinsic reward systems to be difficult to set up	Employees react less radically to anxiety due to stability	Not clear who role models are outside of the organization	Identifying where specific data capabilities are in the organization
The Small Organization	HE	F	HE	E	HE	E
Main Quality (when using the tool)	Few people and focused activities allow for high consistency in attention	Message is communicated strongly when a few data projects is clearly represented in a small budget	Able to reward at every level of the organization	High flexibility and able to adopt and try new solutions fast in a chaotic environment	Top management is very visible to the entire organization, making the mechanism effective	Naturally learning fail fast and common language characteristics
Key Challenge (when using the tool)	High replacement rate and sudden focus change makes it more difficult to be consistent	Not able to allocate for *many* different data initiatives to increase the odds of success	Likely not able to afford extrinsic rewarding	Creating insightful data solutions to problems	Being strategic and smart about role modeling in a very transparent organization	Acquiring formal and costly training

The table provides a general look on how implementation of the mechanisms and actions we suggest is very conditional on some main features of the organizations. We discover some general trends. Financial strength is expressed as an excellent ability to allocate for experimentation and acquire retraining and recruitment capabilities. Flexibility is a good trait to have when developing fail and learn fast characteristics. Size appears in different situations: distance between C-level and business units makes top managers less visible and able to act – it also becomes more difficult to acknowledge employees at every level and be consistent in what is paid attention to, if there are many people to consider. Next, bureaucracy seems to be challenging to a data culture transition; it becomes more difficult to establish decision-making- and fail and learn fast characteristics if processes are slow and influenced by many decision-makers at different levels. Finally, existing data capabilities creates a good foundation for demonstrating success of data technologies when developing initiatives for business units or solutions in times with high anxiety.

On the next page, in Findings Table 2, we summarize the answers to the question we ask in the beginning. We order them from Highly Effective and Effective to Friction. We view this as a high – medium – low scale. We must stress that the extent of "how effective" a mechanism is in a specific setting is not known to us, and therefore we categorize them after how well they synergize with typical company traits. In addition, just because we find friction between a mechanism and an organizational typology, it does not mean the mechanism is not useful to this type of organization. Even in these cases, we point to qualities in the companies that could be used to support use of the mechanism.

Findings Table 2

	HE (Highly Effective)	E (Effective)	F (Friction)
The Large Organization	Allocation, Acquire	Acknowledge, Anxiety	Attention, Act
The Government Organization		Allocation, Act, Acquire, Acknowledge	Attention, Anxiety
The Small Organization	Attention, Acknowledge, Act	Anxiety, Acquire	Allocation

The main point of how different types of organizations react to the 6A framework is visualized in the above table. The mechanisms are distributed fairly unique to each company and we are able to identify some overall patterns. First, the polarity between a large and a small company is expressed by a mirrored distribution – except for acknowledge and acquire. In this instance, being either a small or large organization also has qualities unique to them, which makes them excel in some areas others do not. The large company is able to acknowledge extrinsically with its financial strength, while the small company has limited funds, they are flexible and able to acquire characteristics and talent through fast learning. But most obvious are the polar relationships. A leader in a small company is more visible and therefore immediately impactful and able to display consistency in what is paid attention to because focus is narrower. Lastly, the fewer levels in the organization are accessible when acknowledging desired behavior among employees at every level with great opportunity to reward intrinsically. As a result, smaller companies may naturally develop common language and fail and learn characteristics faster. On the contrary, a leader in the large organization will have a good foundation to allocate for experimentation, failures and talent in the workforce to send a strong financial message of company values. Experimenting and learning from failures while thinking about needed talent are key characteristics in the data culture.

In addition, to support our claim of how different organizational typologies interact differently with the mechanisms in the 6A framework, we include a government-funded company with a third set of unique traits. Here, conflict mainly rise around its decision-making structure, inflexibility and with its invisible leaders outside of the organization, all mainly related to bureaucracy. However, the company shares some of the benefits of being a smaller company, such as the ability to focus its attention and offer intrinsic rewards. We could also imagine that the company possibly had access to a lot of data from governmental partners or similar. The government organization is in fact the only hypothetical with four mechanisms in the "effective" category. It is likewise the only company without a "highly effective" mechanism. This indicates that this type of company has a lot of potential, but some things might be suppressing its potential, such as bureaucracy and inflexibility. Though there are most likely many more factors and traits in play in an organization, part of a larger government eco-system with its own macro culture, which we do not account for. However, the key learning here is maybe not to consider whether this company reflects a government-controlled company in the real world but rather testing the impact of bureaucracy and inflexibility when using the 6A framework. It becomes clear that different types of organizations develop data culture differently – meaning with different mechanisms. We imagine that for example a middle-sized company, non government-owned, would have stronger financial resources than The Small Organization, and at the same time, not be "as encumbered as larger companies by legacy systems or layers of hierarchy" (Ritter et al., 2017, p. 9) which positions a middle-sized company with great and agile characteristics, perhaps enabling this type of organization to be most successful with the implementation of various 6A mechanisms. However, based on the types of organizations and their unique transitioning into a data culture, it puts a lot of strain on the framework as it must cater and offer tailored actions to these very different organizational typologies. Something the framework, at its current stage, is not equipped for. However, this insight is exciting too because there is absolutely no limit to the number of actions one could fit under each of the six mechanisms. We provide one to each data culture characteristic derived from the literature, some actions clearly more approachable and stronger than others. Several actions involving collaboration were not included, such as; allocate for and acquire collaboration skills across business units, acknowledge collaborative behavior inter alia. For future research, adding new actions to the 6A framework and, maybe more importantly, directing them at specific organizational typologies will increase the dynamic of the framework, making it more applicable to real world organizations looking to nurture a data culture. We consider it is worth for other researchers to look at existing organizational typology-frameworks, such as Miles and Snow's four strategic types (1978), in relation to our research. The large-, government- and small company in our discussion share resemblance to the defender-, reactor- and prospector types in the same order. In the light of our findings, it becomes clear that the 6A framework, or any future data culture development tool, should address this nuance in order to be complete. In addition, we have included the most obvious key challenges for the three companies in Findings Table 1. Others may use it for inspiration and create actions to solve the most realistic ones.

8. Conclusion & Implication

The aim of this thesis is to identify and examine how organizations successfully can gain more from data analytics. We come across the surprising fact that most companies are not able to take advantage of what data analytics has to offer. We further scope the problem and find that current theoretical tools are overlooking cultural components and understating their importance. Our research indicates that a healthy culture might be a necessary condition if initiatives in other big data domains are to succeed.

Throughout this paper we seek to contribute new knowledge to existing literature when approaching this disconnection pragmatically. We have been collecting various key definitions and names from authors for organizational culture in a big data setting. We introduce a collective term out of necessity and convenience and call it a data culture. We further identify three main characteristics that constitute a so-called data culture: (1) making decisions based on data, (2) failing fast and learning from it, and (3) having a common language and ability to speak about data. Our main contribution is the 6A framework, able to develop these organizational characteristics in a practical and approachable way through action based suggestions. The main purpose of the 6A framework is to provide leaders with a tool to promote data culture transition. We develop this for leaders to use, as we find that top management play a critical role for driving and facilitating change in organizations. We built the framework based on ideas of the most prominent scholar in organizational culture, Edgar Schein and his six culture embedding mechanisms for leaders. These mechanisms are concrete tools for leaders at any level of an organization to use to manage organizational culture. We modify and translate these mechanisms to address the three characteristics of a data culture. We further change the names of the mechanisms to something more memorable, for better usability as we are developing with managers in mind. We gather the six mechanisms to create the name the 6A framework. We suggest actions for each characteristic based on systematic coding and categorizing documents collected from three large consultancy databases. We further discuss the framework against three generic hypotheticals with typical traits: a small-, large- and government-owned organization. We note from the discussion that the six embedding mechanisms are not equally effective or implementable to different organizational typologies and that there is a need for research on how data culture development is influenced by general conditions of a company. We have suggested to look at how data culture development is either constrained or facilitated in different organizational typologies through other frameworks, such as Miles and Snow's organizational strategies.

8.1. Limitations

We acknowledge the main problem of doing theoretical research and question how effective the 6A framework is in a real-world setting. We seek to accommodate this by discussing the framework against three hypotheticals, all resembling typical companies in general ways. However, it is difficult for us to consider the actual validity of this process. The more obvious approach to the problem statement is an action research strategy. We would ideally have liked to work closely with leaders and members of organizations in developing, testing and improving the 6A framework continuously. Though we do use ideas from action research, as we develop iteratively and through many versions, each with an evaluative phase at the end. We scope our research to not address neither macro or subcultures or discuss the concepts in relation to our framework. As a result, it is unsure to us how the 6A framework will be applied by leaders across borders or how effective the frame is in aligning and managing subcultures.

In summary, working in close collaboration with an organization was not possible given the current COVID-19 situation where we understand that organizations must prioritize differently. We adapt to the situation by making it a goal to do some of the groundwork and provide something tangible for future researchers to work on. We believe that by collecting a lot of valuable newer research in conjunction with the work of Schein, the 6A framework is able to function as a good starting point for providing actionable steps for leaders on all levels of an organization. The framework underlines that leaders must bring attention to aligning culture with business strategy in order to transition into a culture that is able to make data analytics the competitive weapon it has the potential to be.

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Appendix

1: We developed a crisis plan when the lockdown emerged (in Danish)

Scenarie	**Løsning**
En bliver syg men ikke den anden	Hvis vi har haft mødtes i den periode hvor den ene bliver erklæret syg, så skal begge i karantæne 14 dage og se om man får symptomer osv. Hvis den syge føler sig rask nok, så holder vi skype-sessions og arbejder hjemmefra, så vi ikke kommer bagud.
Begge bliver syge	Begge i karantæne 14 dage. Hvis vi kan (ift. hvor syge vi er) så holder vi Skype-sessions og arbejder hjemmefra, så vi ikke kommer bagud.
Ingen er syge, men begge i karantæne	Skype-sessions og laver alt det vi kan hjemmefra. Alt arbejde rykkes over på digitale tjenester som Drive, Skype (Messenger) osv. og møderne fortsætter som normalt - online.
CBS/Biblioteker/Åbne institutioner lukker	Alt arbejde rykkes over på digitale tjenester som Drive, Skype (Messenger) osv. og møderne fortsætter som normalt - online. Vi vil gerne overveje steder (som ikke er tæt befolket) der alligevel er åbne, så muligheden for at møde fysisk stadig er der (evt. hjemme hos en af os eller hvis man kan booke lokaler steder)
Ingen fysiske interviews	Tænke i alternative løsninger; vi kan eksempelvis lave skype-interviews eller mail-interviews med virksomheder.
Hvis ingen virksomheder vil deltage	Overveje at sample uden for virksomheder og efter stillinger. Der er ingen grund til, at vi har brug for fag-professionelle fra én bestemt virksomhed.
Ingen dataindsamling	Møde med vejleder/samtale med CBS for løsningsmuligheder. Hvis ikke muligt at løse uden at gå på kompromis med resultatet; overvej at udskyde
Kreative processer (som framework) uden fysisk samvær	Skype-sessions og Google Tegninger, så vi kan sketche samtidig med vi Skyper.

2: Loose and more detailed sketches, collage