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Data Driven Decision Making:
Organizational factors influencing the adoption and implementation of Data Driven Decision Making.

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ABSTRACT (MAX. 200 WORDS):
Decision making is one of the most critical tasks that can have an impact on organisations' performance. To rely on decisions, organisations need to consider effective decision making. Hence to make effective decisions, most organisations are moving towards data driven decision making with the aim to increase profits and reduce costs that can lead them to a competitive advantage. However, adopting and implementing data driven decision making has been a challenge for most organisations resulting in high failure rate in implementation of data driven decision making. This paper identifies and describes organisational factors that are influential in the implementation of data driven decision making. A qualitative research using seven semi-structured interviews with data analytics consultants and decision makers was conducted. The conclusion shows that management support, availability of skills, change management, organisational size, industry or sector, perceived value, organisational culture and organisational structure and processes are factors that have an impact in the adoption and implementation of data driven decision making. Thus, these findings can be used by other researchers as a reference for further research on the topic.

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1 Introduction

Decision making is one of the most important tasks in organisations and it has far reaching impact on organizational performance (Sharma, Mithas & Kankanhalli, 2014). However, according to research by Clemons, Eric, Dewan, Robert, Weber and Thomas (2017), it has been a challenge for organisations to make reliable decisions since human beings are unreliable decision makers. To mitigate this, organizations are moving towards data driven decision making (DDDM), a way which helps them make informed decisions based on their data (Chen, Preston & Swink, 2015). Based on a survey of over 4,000 IT professionals from 93 countries and 25 industries, Chen, Chiang and Storey (2012) found that DDDM has been one of the major technology trends for efficient decisions in organisations since 2010. Since then, more organizations profess themselves to be data driven as they have realised competitive advantages of implementing DDDM (Jha, Agi & Ngai, 2020). Because organisations are leveraging data for decision making, data became one of the most valuable assets that any organization would wish to possess (Raguseo & Vitari, 2018). In 2017, The Economist published the article “The world’s most valuable resource is no longer oil but data” where data is described as a new commodity in a rapidly expanding industry, a commodity that was named oil a century ago (Parkins, 2017).

According to the industry leading-survey, 49% of the leading organizations such as Facebook, Google and Amazon use data to improve their decision-making processes (Stobierski, 2019). Today’s largest and most successful organizations use data to their advantage when making high impact decisions (Jha, Agi & Ngai, 2020). Hence, increased use of data driven decision making (DDDM) technologies would benefit organizations’ decision-making processes. Moreover, by using DDDM, organizations run their operations through business processes that are designed to achieve their objectives (Jha, Agi & Ngai, 2020). In addition, a variety of decisions are involved in business processes, such as choosing a path from among several options, deciding on quantities, and allocating resources. These decisions have an impact on the process outcomes and ability to achieve its goal (Chen, Preston & Swink, 2015).

Although there are noticeable advantages of becoming data driven for decision-making, there is still high failure rate when implementing DDDM in organizations (Clemons et al, 2017). According to a survey in 2017 by Halper and Stodder (2017), only 25% of organizations which implemented DDDM were able to reach their objectives and realize the value of their investment. Based on surveys from 2017 to 2020 by Halper and Stodder (2017) and Jha, Agi and Ngai (2020), the improvement rate at which organizations are implementing DDDM successfully is still nominal where by only 30% of them managed to gain value from their DDDM investment in 2020 (Jha, Agi & Ngai, 2020), resulting in only 5% improvement between 2017 and 2020. This is due to limited research that can be used as a reference guide by organizations to successfully implement DDDM. Hence, a qualitative study was done in which semi-structured interviews were conducted. Consultants involved in the implementation of DDDM and decision makers from various Swedish organisations in different industries were interviewed. Thus, through empirical results, this paper identifies factors that have an impact in the implementation of DDDM which are management support, organisational support, availability of skills, organisational size, change management, organisational culture, industry or sector and perceived value. In this paper, we refer to the adoption and implementation as the end-to-end process that the organisation has to follow from decision to adopt to infusion of the technology within the organisation (Cooper & Zmud, 1990).

1.1 Problem

Many studies have identified and documented the benefits of adopting data-driven decision making (DDDM) which include fast decision making and improved decision quality which can lead to increased productivity, improved financial performance and increased competitive advantage (Berntsson Svensson & Taghavianfar, 2020; Grover, Chiang, Liang & Zhang, 2018; Jha, Agi & Ngai, 2020; Müller, Fay & vom Brocke, 2018). The prospect of improved business performance through the incorporation of Big Data Analytics in the decision-making process has motivated organizations to invest in DDDM implementation projects (Berndtsson, Lennerholt, Svahn & Larsson, 2020; Berntsson Svensson & Taghavianfar, 2020; Mikalef, Pappas, Krogstie & Giannakos, 2018). To date, several organizations are claiming to be data-driven, that is, they are already making use of their data in their decision-making process (Berndtsson et al., 2020).

However, despite the documented potential benefits of becoming data-driven, the transition to become data-driven has proven to be a major huddle for most organizations (Berndtsson et al., 2020). “Leading corporations seem to be failing in their efforts to become data-driven” (Bean & Davenport, 2019, p.3). According Berndtsson et al. (2020), around 30% of organizations had successfully shifted to become data-driven while the remaining had either faced challenges or had not kicked off the transition. Some studies have also shown that most of the organizations that have invested BDA have yet to realise the benefits with only 25% claiming to have improved their outcomes (Ghasemaghaei & Calic, 2019). Adrian, Abdullah, Atan and Jusoh (2017) highlighted that many organizations have struggled to get past the implementation phase having encountered deployment challenges. There is lack of understanding on how organizations can implement their Big Data solutions to support their corporate decision-making (Jha, Agi & Ngai, 2020).

The poor success rate in implementing data driven decision making can be attributed to lack of academic research on the prerequisites and enablers of data-driven decision making in companies (Jha, Agi & Ngai, 2020). This lack of research “leaves practitioners in unchartered territories when faced with implementing such initiatives in their firms” (Mikalef et al., 2018, p.548). The few studies available on this topic have mainly focused on the technological factors affecting the implementation of data driven decision making including infrastructure, data processing techniques and tools (Berntsson Svensson & Taghavianfar, 2020; Svensson, Feldt & Torkar, 2019). This leaves a significant gap in the literature as it has been noted that it takes more than the technological factors to successfully implement data driven decision making. According to a survey cited by Bean & Davenport (2019), only 7.5% of executives considered technology to be an obstacle while people and processes were cited as a challenge by 93% of the interviewees. Organizational factors such as people, availability of skills and management support have been known to affect the implementation of data driven decision making (Berntsson Svensson, Feldt & Torkar, 2019; Mikalef et al., 2018). Berndtsson et al. (2020) highlights the need for researchers to investigate paths and steps organizations can take to utilize their data.

In summary, the problem we identified is that there is a documented high failure rate in organisations’ adoption and implementation of data driven decision making. Also, we identified a research gap on influential factors in implementing data driven decision making. Of the limited literature available, most focus on technological factors and very few focuses on non-technological factors like organizational factors. Therefore, our study identifies and describes organisational factors that are influential in the adoption and implementation of data driven decision making.

1.2 Research Question

This research aims to answer the research question:

1. What organisational factors are influential in the implementation of data driven decision making (DDDM)?

1.3 Purpose

This thesis aims to identify and describe the organizational factors that influence the adoption and implementation of data driven decision making (DDDM). Given the research gap on the topic, the thesis will contribute to the literature exploring what it takes for organizations to become data driven. Researchers and scholars can reference and build on to this research to conduct more research to enhance understanding on the topic. Also, practitioners can use this paper as reference while developing and implementing data driven decision making solutions.

1.4 Delimitation

Tornatzky and Fleischer (1990 cited in Entzenberg & Söderqvist, 2020) proposed the TOE framework that classified technology adoption factors into Technological, Organisational and Environmental (TOE) factors. Our study focused on organisational factors only, that is organisational factors that are influential in the adoption and implementation of data driven decision making. First, the research gap we identified showed a lack of studies identifying organisational factors in data driven adoption. Second, focusing on organisational factors allowed us to narrow down a broad topic to allow us to be detailed in our study.

2 Literature Review: Data Driven Decision Making

In this chapter, existing literature related to data driven decision making (DDDM) adoption and implementation was reviewed. First, we looked at the broad topic of organisational decision making, and challenges associated with it. Second, we reviewed literature on Big Data and Big Data Analytics as a critical component of data driven decision making. Third, we narrowed down to data driven decision making in organisations which is the use of data including Big Data in organisational decision making. Finally, we presented organisational factors which are influential in the adoption and implementation of technology as highlighted in existing literature. The findings of this literature review that is themes and concepts were used to guide the empirical research conducted in this study.

2.1 Organizational Decision Making.

Many studies by researchers from different fields have put forward different definitions of decision making in the organisational context. Simons and Thompson (1998) defined decision making as the act of seeking and interpreting information with a goal of arriving at conclusions based on the information and perceptions. Also, organisational decision-making can be referred to as a process that involves evaluation of possible options using knowledge, structure and data of the organisation to predict the best choice suited for a particular objective (Kulkarni et al., 2015; Shollo & Galliers, 2016). “A decision is a commitment to a course of action that is intended to produce a satisfying state of affairs” (Yates, Veinott & Patalano, 2003, p.15). The aim of the decision-making process is to answer the questions:

> what decisions must be made, who will make them, how and what resources will be allocated, and how the situation will be measured and revisited in the dynamic environment in which the system will be operating (Bhushan & Rai, 2004, p.vi).

Decisions can be made by individuals or can be made by teams, they can be once off or repetitive or a combination of smaller assessments and choices (McKenzie, van Winkelen & Grewal, 2011). What is consistent in most of the definitions is that the decision-making process involves assessment of information and options available to pick the option that is deemed to provide the best outcome. Overall, decision making is an important aspect of every organisation hence ill-informed or poor quality decisions can negatively impact the organisation’s performance (McKenzie, van Winkelen & Grewal, 2011). Decision making is considered the most important task in organisation with far reaching consequences on the organisation (Sharma, Mithas & Kankanhalli, 2014). As such, efforts to improve decision quality have been made in both research and organisations.

2.1.1 Types of decisions in organisations.

Laudon and Laudon (2002) classified organizational decision-making into four categories namely strategic decision making, management control, operational control and knowledge-level decision making. First, they described strategic decision making as the process of determining organization’s policies, resources and objectives on a long-term basis. Taylor and

Purchase (2016) also describe strategic decisions as infrequent and unique decisions usually made by executive management in board meetings. Second, management control focuses on the efficient and effective use of resources as well as performance of operational units. Third, operational control decisions dictate how specific tasks are to be carried out as well as the completion criteria and resources required. Operational decisions are smaller and repetitive decisions which are often automated (Taylor & Purchase, 2016). Lastly, knowledge-level decision making looks at the evaluation of new ideas, products and services including ways to share information across the organization.

Within the categories, decisions can be further classified into structured and unstructured decisions (Laudon & Laudon, 2002). Structured decisions follow a definite handling procedure and are known to be repetitive and routine (Laudon & Laudon, 2002). On the other hand, unstructured decisions are nonroutine and they require insights, evaluation, and judgement each time they are made (Laudon & Laudon, 2002). While both structured and unstructured decisions are found in all four categories, majority of strategic decisions are highly unstructured, and majority of operational decisions are fairly structured.

For our empirical study, we considered two categories which are strategic decisions and operational decisions. We looked at strategic decisions as long-term decisions while operational decisions are smaller, repetitive short-term decisions as both Laudon and Laudon (2002) and Taylor and Purchase (2016) highlighted.

2.1.2 Challenges in Organisational Decision Making: Uncertainty, Equivocality and Complexity.

Decision making is considered to be one the most challenging roles of managers in organisations (Laudon & Laudon, 2002). There are several reasons why decision making in organisations is complex and these include uncertainty and equivocality (Daft, Lengel & Trevino, 1987). First, decision makers have to deal with the uncertainties in organisation (McKenzie, van Winkelen & Grewal, 2011). Organisations face many forms of uncertainties frequently and these can be about markets and suppliers or stakeholders in general (Choo, 1991). The goal of decision makers is to reduce uncertainty as much as possible and this can be done by using as much information as possible in decision making (Agarwal & Tanniru, 1989). As the amount of information available increases, the level of uncertainty decreases (Daft, Lengel & Trevino, 1987).

The issue of equivocality in organisation also complicates the decision-making process as decision often have to be made by teams made up of individuals with different frames of reference and expertise (Daft, Lengel & Trevino, 1987). "Information equivocality is defined as the multiplicity of meaning conveyed by information about organizational activities" (Daft & Macintosh, 1981, p.211). This means there can be multiple and conflicting understanding of the situation leading to confusion and disagreement among decision makers (Daft, Lengel & Trevino, 1987). Equivocality often leads to exchange of subjective opinions among decision makers to reach conclusions (Daft, Lengel & Trevino, 1987). Like uncertainty, it is important for organisations to reduce equivocality to improve the decision making process (Choo, 1991). Different departments in organisations can develop different goals, language and attitudes therefore it is important to reduce equivocality by leveraging on rich information processing (Choo, 1991).

Decision makers also have to make decisions in different contexts of varying complexity including simple contexts, complicated contexts, complex contexts and chaotic contexts (Snowden & Boone, 2007). Snowden and Boone (2007) described simple contexts as stable with a clear cause-and-effect relationship where the right answer is self-evident. They described complicated contexts as ones in which there are multiple right answers and the cause-and effect relationship requires some form of analysis to reach a conclusion. In complex contexts, the right answer cannot be ferreted out and the situations can only be understood in retrospect (Snowden & Boone, 2007). On the extreme end, chaotic contexts are turbulent situations in which the patterns shift frequently and the right answer is impossible to find (Snowden & Boone, 2007). It is important for decision makers to use their experience recognise the context and respond appropriately for each context (McKenzie, van Winkelen & Grewal, 2011). According to Snowden and Boone (2007), most organisational decisions are complex as they involve some unpredictability and flux. Also, organisation leaders need to have the ability to handle the crisis nature of chaotic decision making contexts and minimise damage in such situations (Snowden & Boone, 2007).

Overall, organisations are making efforts to reduce the effect of uncertainty, equivocality, and complexity in their decision-making process. Becoming data driven is one of the most cited solution to minimise challenges in decision making and improve decision quality as discussed in section 2.3.

2.2 Big Data in Organisations

2.2.1 Big Data

Over the last decade, there has been an unprecedented increase in data volume, variety, and velocity, a phenomenon known as "Big Data" (Sivarajah, Kamal, Irani, Weerakkody & Vishanth 2017). According to Austin and Kusumoto (2016) “Big Data (BD) can be defined as information asset which is characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value”. Big Data can be explained as the 3Vs which are Velocity, Variety and Volume. Hence, the 3Vs are described in this section of the paper.

Velocity refers to the rate at which the data is being received. This means data will be generated and collected at a very fast rate during the real-time streaming as some smart products which uses internet operate in near real-time or real time that needs immediate action (De Mauro, Greco & Grimaldi, 2016). For example, the rapid rate at which Facebook and Twitter receives data per second through videos, messages and photos from all its users in the whole world (Gong, Xi, Yang & Xining, 2020).

Volume refers to large amounts or magnitude of data that is being received (Austin & Kusumoto, 2016). More data is being produced at a rapid pace, resulting in massive amounts of data to be processed. For example, the amount of data that is generated on daily basis in Europe through credit card transactions is huge.

Variety refers to various types of data being generated either as videos, messages, text or photos (De Mauro, Greco & Grimaldi, 2016). All this type of data can be classified into structured, semi-structured, unstructured and mixed data as they all come from different sources (Austin

& Kusumoto, 2016). Thus, Big Data comprises of huge amounts of data from various data sources which is generated at a rapid rate.

2.2.2 Big Data in Organisations

It is imperative for organisations to come closer to their customers and adapt to the changing business environment (Raguseo & Vitari, 2018). Decisions need to be made faster and with higher accuracy than ever before (Pauleen & Wang, 2017).

As the modern world generates a staggering quantity of data, BD has been regarded as a game-changing technological development in organisations (Kitchens, Dobolyi, Li, Jingjing, Abbasi & Ahmed, 2018). The availability of tremendous amounts of data provides unprecedented opportunities for organisations. According to Mlitz (2021), big data is expected to grow from $64 billion in 2021 to a $90 billion industry by 2025.

Rapid accumulation of various types of data from different sources has been a driving force for an increasing interest in BD and business analytics for decision making (Abbasi, Zahedi, Fatemeh, Chen, Yan, Hsinchun & Jay 2015). When compared to rivals, the ability to easily process larger volumes of data allows organisations to make better-informed decisions in less time (Berntsson Svensson & Taghavianfar, 2020). This demonstrates that big data has emerged as a new powerful source of potential enormous economic and social value, as well as a source of gaining a competitive advantage for organization's capital assets and human talent (Raguseo & Vitari, 2018). BD is increasingly becoming important to organisations for a variety of reasons, of which decision making is one of the most important reasons. However, for organisations to benefit from big data, they need to make use of data analytics technologies and techniques to analyse data sets and gather insights for decision making (Abbasi et al., 2015). Hence, Big Data Analytics (BDA) plays a vital role in converting big data to something of value to organisations.

2.2.3 Big Data Analytics

Big Data Analytics (BDA) is the use of statistical techniques, and analytics methods to improve businesses by analysing Big Data (Sivarajah et al., 2017). These techniques and methods vary from the most basic, "descriptive analytics," which entails preparing data for further study, to "predictive analytics," which uses sophisticated models to forecast and predict the future, to "prescriptive analytics," which employs machine learning algorithms and dynamic rule engines to provide interpretations and recommendations (Sivarajah et al., 2017). All these types of data analysis lead to smarter business moves, higher profits, cost reduction, optimization of business operations by analysing customer behaviour, and effective decision making as they assist organisations in harnessing their data and identifying potential opportunities (Lash, Michael, Zhao & Kang, 2016).

Depending on the type of Big Data Analytics being used by an organization. There are various BDA use cases that play an important role in our daily lives. These use cases are Fraud Prevention, Security intelligence, Price Optimization, Recommendation Engines, Social Media Analysis and Response and most importantly decision making. However, this study focuses on decision making as one of the most important use cases of Big Data Analytics.

2.3 Data Driven Decision Making in Organisations

Many scholars have highlighted the importance decision making in organisations. The quality of decisions has been strongly linked to the productivity, competitiveness, efficiency and profitability of organisations (Berntsson Svensson & Taghavianfar, 2020; Lindgren, 2019; Shollo & Galliers, 2016). However, many authors such as Daft, Lengel & Trevino (1987), Choo (1991) and Snowden and Boone (2007) have highlighted serious challenges in organisational decision making including uncertainty, equivocality and complexity. These challenges are expected to have increased in recent years due to increased organisations size, pressure from competition, availability of vast amounts of data and the need to make real-time decisions in some instances. Researchers have explored several ways of making the organisational decision-making process keep up with the ever-changing needs and situations.

There is a lot of literature that has linked the use of data in decision-making process with improved decision quality and as a result, improved organisational performance (Hedgebeth, 2007; Müller, Fay & vom Brocke, 2018; Power, 2008). Big Data and Big Data Analytics have been widely regarded as an opportunity to improve decisions (Berntsson Svensson & Taghavianfar, 2020; Ghasemaghaei & Calic, 2019; Müller, Fay & vom Brocke, 2018). On the other hand, decision making has been cited as the single most important use case of Big Data and BDA (Berntsson Svensson & Taghavianfar, 2020). There is a consensus in literature on the value of incorporating data in the organisational decision-making process.

Treder (2019) says data can provide insights which can lead to well informed decisions. Adding that informed decisions is the ultimate value contribution of data. Data is an important aid to the decision makers which they can use alongside instincts and other knowledge sources (Kumaresan & Liberona, 2018). Shollo and Galliers (2015) recognised and acknowledged the role of Business Intelligence systems in supporting decision making with better information and time saving capabilities. Organisations are increasingly incorporating Big Data in their strategy realising the potential to improve their decision making and enhancing their competitiveness (Berntsson Svensson & Taghavianfar, 2020). Big Data and Big Data Analytics (BDA) have gained attention as organisations from different industries seek to take advantage of the influx of data and become data driven (Berntsson Svensson & Taghavianfar, 2020).

Many terms have been used to refer to the organisations' incorporation of data in decision making process. Data Driven Organisation (DDO), Data Driven Decision Making (DDDM), and Big Data Analytics (BDA) are among the commonly used terms.

An organisation can be considered to be data-driven "as soon as data is broadly accepted as a relevant contributor to decision-making, at all levels of the organisation" (Treder, 2019, p.135). Berntsson Svensson and Taghavianfar (2020) define a DDO as an organisation that uses a combination of data sources to make decisions. Becoming a DDO involves fostering a data-driven culture in which data is collected and analysed to inform decisions (Berntsson Svensson & Taghavianfar, 2020). In this culture, data is prioritised over opinions when making decisions (Berntsson Svensson & Taghavianfar, 2020). In a DDO, data is used to drive action, "even if that action is a deliberate inaction" (Berntsson Svensson & Taghavianfar, 2020, p.4). Another key characteristic of a DDO is the availability and accessibility of data by individuals who need to analyse it and make effective decisions (Kumaresan & Liberona, 2018). In a DDO, data is a key component of the decision-making process while observations and intuition always come after data insights (Berntsson Svensson & Taghavianfar, 2020).

Müller, Fay and vom Brocke (2018) define data-driven decision making (DDDM) as the use of data and business analytics to make decisions. This is coherent with the DDO description in other literature and a DDO can be considered to be an organisation that practices data-driven decision making (DDDM).

Data is an important component of DDO and this can be seen in literature focusing on Big Data and BDA in which decision making is recognised as the single most important outcome of BD and BDA. Janssen, van der Voort and Wahyudi (2017) highlight how organisational decision making can be transformed by tapping into large-scale, fast-moving, complex streams of datasets also known as Big Data. Big Data and BDA is a critical component in the transformation into a DDO and organisations who intend to transform into DDO need to understand Big Data and BDA in detail (Berntsson Svensson & Taghavianfar, 2020). Treder (2019) refers to data as a magical, intangible material that can be used to improve decision making. Data have massive potential to complement decision makers' experience and intuition (Treder, 2019). Many organisations have invested in BDA as a way to guide their decisions and improve business performance (Grover et al., 2018).

2.3.1 Data Driven Decision Support Systems

The use of computers to support decision making is not a new technology. Bonczek, Holsapple and Whinston (1979) highlighted the bond that had formed between computers and decision maker. Even back in the seventies, computers had become so important in supporting decisions beyond mere information retrieval (Bonczek, Holsapple & Whinston, 1979). There are several types of computerized decision support systems which include data-driven decision support systems (Power, 2008). In our study, we focused on data-driven decision support systems as a way of supporting data-driven decision-making. Power (2002 cited in Power, 2008, p.149) defines a decision support system (DSS) as "an interactive computer-based system or subsystem intended to help decision makers use communications technologies, data, documents, knowledge and/or models to identify and solve problems, complete decision process tasks, and make decisions". From this definition, a data driven DSS is a type of DSS which makes use of data to support decision making. Data-driven DSS range from basic tools searching a simple file system to more sophisticated systems including data warehousing and online analytical processing (OLAP) capabilities (Hedgebeth, 2007). Business Intelligence (BI) is a term that is commonly used alongside DSS. According to Power (2008), a BI system is a data driven DSS which consumes historical data to generate reports.

In our study, we recognised the need for a data driven DSS for an organisation to become data driven. From the simplest form of data driven DSS to the modern and sophisticated DSS including large data warehouses, we aimed to study what it takes for organisations to become data driven. Adoption and implementation of data-driven decision making involves adopting and implementing one or more data driven DSS. However, as demonstrated in section 2.5 using the IT implementation developed by Zmud and Apple in 1989 (Cooper & Zmud, 1990), becoming a data driven organisation takes more than just adopting a data driven DSS.

2.4 Organizational Technology Adoption and Implementation

While adopting a data driven DSS is critical in the adoption of data driven decision making, organisations need to do more than just implementing the technology for them to extract full value. There is need to properly incorporate the technology into the organisation for it to deliver real value (Cooper & Zmud, 1990). A model for IT implementation developed by Zmud and Apple in 1989 cited by Cooper and Zmud (1990) provides a six-stage process followed when implementing technology innovation (see Figure 2.1). The process includes initiation, adoption, adaptation, acceptance, routinisation, and infusion. The first step in the process is initiation which involves organisational problem and opportunity identification as well as finding a suitable IT solution. Second, during the adoption stage, a decision is made for the organisation to invest resources in the implementation of the technology. Third, the adaptation stage involves the delivery of the technology, adjustment of organisational processes and training the members of the organisation. The fourth stage, acceptance, is where the users accept the technology and start using it. The routinisation stage of the process involves the continued use of the technology as part of the normal processes and the technology is accepted as an ordinary system with all the governance processes in place. Finally, infusion stage is when the technology is now being used to its full potential and the organisation is now realising the benefits like effectiveness among many. The organisation's potential to realise benefits from technology implementation is dependent on how well the technology has been embedded into the organisation's processes or how well the organisation manoeuvred through the six stages (Cooper & Zmud, 1990). The implementation of Data Driven Decision Making, like any other Information Technology, follows the six stages of Zmud and Apple's IT implementation technology. At each stage, there are factors that influence the outcome.

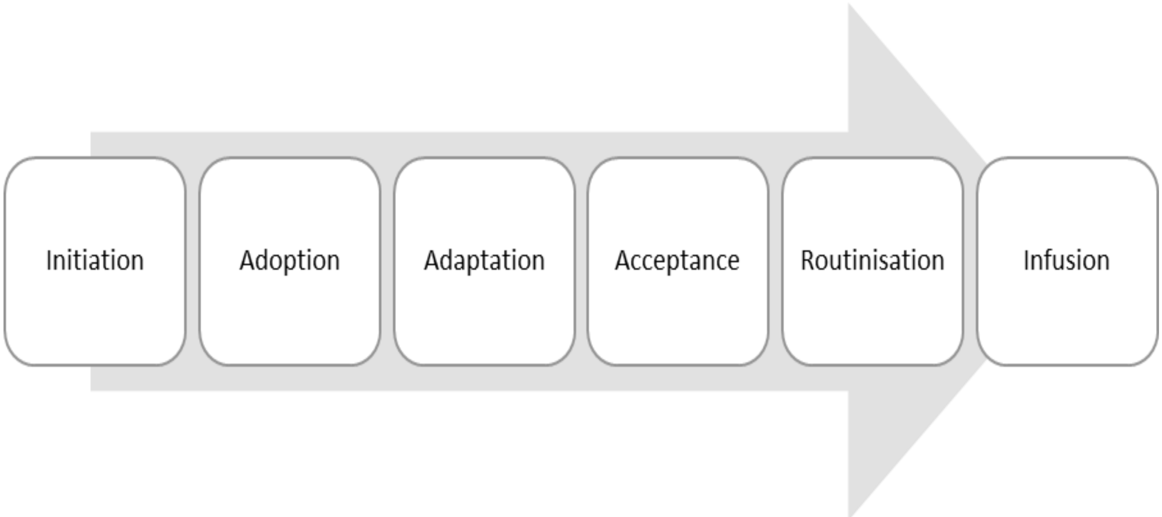

Figure 2.1: A representation of IT Implementation Model (adapted from Cooper & Zmud, 1990)

With regards to factors influencing the adoption process, Tornatzky and Fleischer (1990 cited in Entzenberg & Söderqvist, 2020) proposed the Technological, Organisational and Environmental (TOE) framework. The TOE framework classifies the factors that affect an organization's technology adoption and implementation into three categories which are technical, organizational, and environmental factors (Baker, 2012). The availability of related technology and the characteristics of the available technologies are under the technological factors (Baker, 2012). Also, the structure, procedures, scale, and lack of resources of an organization are within the organizational factors (Entzenberg & Söderqvist, 2020). Lastly, the external factors influencing the organization, such as suppliers, competition, and legislation, are referred to as the environmental factors (Entzenberg & Söderqvist, 2020). This study focuses on the organizational factors that influence the adoption and implementation of data driven decision making.

2.4.1 *Organizational Factors in Technology Adoption and Implementation*

Many studies have identified various organisational factors that influence technology adoption and implementation in general. "*Organisational factors refer to the factors that relate directly or indirectly to the structural, operational, human, and managerial sides of the business entity…*" (Alshawi, Missi & Irani, 2011, p.378). Organisational factors can also be referred to as internal factors and they include the organisation's users, structure, processes, size, financial capabilities, and management support (Del Aguila-Obra & Padilla-Meléndez, 2006). While some of these factors were identified in a specific context, for example adoption of a particular technology like Del Aguila-Obra and Padilla-Meléndez (2006) internet technology adoption, this study draws guidance from these past findings. The focus of this study is to identify influential organisational factors in the implementation of data driven decision making. Also, the study will seek to get detailed descriptions of each of the identified organisational factors and situations in which they can provide positive or negative influence on the adoption and implementation. To guide our research, we captured the most common organisational factors identified in existing literature which are management support, organisation structure, organisation processes, organisation size, organisational culture, organisation capabilities, change management, and availability of skills within the organisation.

Management support has been consistently identified in many studies as a top factor in the adoption and implementation of IT technology. Cooper and Zmud (1990) identified top management support as one of the factors that have a significant impact in the implementation of technology. Iacovou, Benbasat and Dexter (1995) highlights that when management recognise the potential benefits of a technology, they are willing to allocate resource and support the adoption. In such a case, the organisation is more likely to succeed in the adoption process. In addition, top executives' attitude towards IT adoption plays a significant role in the adoption of IT by organisations (Mehrtens, Cragg & Mills, 2001). A review of past studies shows that management support is a mandatory requirement to successfully adopt and implement any technology in an organisation. More recent studies like the one by Berntsson Svensson and Taghavianfar (2020) identified lack of management support as one of the top challenges when transforming into Data Driven Organisations (DDO). With management or executive support, the organisation can successfully overcome barriers and resistance that comes during the implementation of DDO (Treder, 2019). The highlighted evidence compelled us to include management support as one of our guiding factors in our research.

Availability of skills has been widely cited as an important factor in the adoption and implementation of technology including transformation to DDO. Mehrtens, Cragg and Mills (2001) classified availability of skills under the organisation readiness to adopt technology. They say the level of IT knowledge among both IT professionals and non-IT professionals determines the readiness of an organisation to adopt technology. Inhouse IT expertise at both employee and management level can help the organisation harness the full potential of IT technology during the adoption process (Fink, 1998). The availability of skills is also recognised as a critical factor in data driven decision making. The ability of decision makers to understands and interpret data during the decision-making process is as important as the availability of data and technology (Svensson, Feldt & Torkar, 2019). In addition, for an organisation to be able to use data in decision making, there is need for analytical skills (Grover et al., 2018; Kumaresan & Liberona, 2018) and lack of skills is a big challenge as the organisation will not know how to make use of its data (Berntsson Svensson & Taghavianfar, 2020). Considering how availability of skills frequently appear in studies about technology adoption and implementation, we sought to investigate the possibility of this factor being influential in the adoption and implementation of data driven decision making.

Organisational Structure and Processes. The adoption and implementation of technology is known to be dependent on the organisational structure and processes (Del Aguila-Obra & Padilla-Meléndez, 2006). The organisational structure can affect the speed at which the organisation can adopt innovations (DeCanio, Dibble & Amir-Atefi, 2000). This will not only affect how fast the organisation adopt technology but will also have potential to impact the success of the implementation. DeCanio, Dibble and Amir-Atefi (2000) further highlight that the structure of an organisation will have an effect on the people and the operational units within it. Adopting a new way of operation introduces change in organisations and the ability of the structure and processes to accommodate the change determines the success of adoption and implementation. When transforming into a DDO, the organisation needs to align its structure and processes to support the data driven culture. Insufficient organisational alignment can be an inhibitor in the DDO implementation (Berntsson Svensson & Taghavianfar, 2020). Changing the business structure is another way of ushering the data driven culture as the existing business setup might not be well suited for the new culture (Kumaresan & Liberona, 2018). One area that the change must address is the shift of accountability when data is the main driver of decisions. Berntsson Svensson and Taghavianfar (2020) suggest that decision makers should not be held accountable for data driven decisions.

Organisation size. Organizational size is an important factor in technology adoption and implementation (Garrison, 2009). However, there is no consensus on how it affects the process. Some argue the bigger the organisation the easier it is to adopt new technology. Proponents of this argument link this to improved capabilities of the organisation in both financial and human resources terms. For example, Garrison (2009, p.445) argues that "*the greater number of individuals employed at a single firm, the more opportunities it will have to discover a new technology*". This view is also supported by Yao, Xu, Liu and Lu (2003) who highlighted the ability of larger firms to leverage on economies of scale to improve the feasibility of technology adoption. On the other hand, some studies argue that smaller organisation are more agile and enjoys the flexibility which is a positive factor when adopting technology (DeTienne & Koberg, 2002). DeTienne and Koberg (2002) argue that as the organisation grow bigger in size and age, it become rigid structurally and the management loses their flexibility to become innovative. In addition, smaller firms are arguably more efficient in adopting innovations because of their less complex communication and coordination channels (Yeaple, 1992). The review of literature shows clear evidence that organisation size is an important factor that can either enhance or inhibit technology adoption and implementation. However, it is not clear in what way this would affect the adoption and implementation of data driven decision making. Our study will seek to establish ways in which the size of the adopting organisation can be a determinant of success or failure.

Organisational culture is known to influence the adoption and implementation of new technology (Del Aguila-Obra & Padilla-Meléndez, 2006). What is organisational culture? There are many definitions of organisational culture but many are centred around the organisation's assumptions, values and artifacts (Parker & Bradley, 2000). For our study, we focused on how organisational values affect the adoption and implementation of technology. The focus on values is grounded on Chatman and Jehn (1994) definition of organisational culture. Organisational culture is defined as the organisation's "widely shared and strongly held values" (Chatman & Jehn, 1994). When adopting new technology, Fink (1998) highlights the need to ensure that the organisational culture is supportive of the adoption. Management needs to be courageous enough to create changes in the culture in order to support Information Technology (Fink, 1998). Organisational culture is also a factor in the transformation to become DDO (Berntsson Svensson & Taghavianfar, 2020). In a data driven culture, employees value data, share data, are open to data and understand the need to use data in decision making (Berntsson Svensson & Taghavianfar, 2020). There is need for a culture shift into a data driven culture without which, stakeholders risk treating Big Data as a threat (Treder, 2019). When making such a significant change in culture, there is a risk of cultural resistance. Cultural resistance to change needs to be handled properly if organisations are to succeed in the implementation of DDO (Berntsson Svensson & Taghavianfar, 2020). A change in culture need to be prioritised as much as strategic and operational changes are prioritised (Kumaresan & Liberona, 2018).

Change Management is required as many organisational changes are needed to embrace the technological innovations introduced by the transformation (Mikalef et al., 2018). Failure to adapt to change is one of the main inhibitors of the transformation process to DDO (Berntsson Svensson & Taghavianfar, 2020). Fear of change is common in organisations and it affects both workforce and leaders (Treder, 2019). To address issues that are related to resistance or acceptance of change, organisations need to perform a comprehensive change management exercise.

2.5 Literature Summary

The aim of this summary is to bring together in short form the topics covered in the literature review. Our research aims to identify and describe organisational factors in the adoption and implementation of data driven decision making (DDDM). To support our empirical research, the literature review covered key topics such as organisational decision making, big data, big data analytics, data driven decision making, data driven organisations, technology adoption and organisational factors in technology adoption. A thematic overview is also presented in Table 2.1 to show the themes and concepts captured from the literature.

In this chapter, we looked at organisational decision making through the works of several authors including Laudon and Laudon (2002) and Taylor and Purchase (2016). Decision making is considered one of the most important processes in organisations where decision makers evaluate options using data to choose the best option for the benefit of the organisation (Kulkarni et al., 2015; Shollo & Galliers, 2016). Decisions can be either structured or unstructured and can be at operational or strategic level (Laudon & Laudon, 2002; Taylor & Purchase, 2016). Strategic decisions are long term organisational decisions while operational decisions are short term decisions usually repetitive (Laudon & Laudon, 2002; Taylor & Purchase, 2016). Laudon and Laudon (2002) also classified decisions based on what they seek to achieve for example management control focusing on resource management and knowledge-level decisions focusing on idea and information sharing.

Decision-making is a complex process which when done well can improve the organisation performance in many ways including increasing productivity, competitiveness, efficiency, and profitability of organisations (Berntsson Svensson & Taghavianfar, 2020; Lindgren, 2019; Shollo & Galliers, 2016). In addition, Daft, Lengel & Trevino (1987), Choo (1991) and Snowden and Boone (2007) cited uncertainty, equivocality and complexity as challenges faced by organisational decision makers. In this study we look at the use of data, particularly Big Data as the most recommended way of improving the quality of decisions in organisations as highlighted by Berntsson Svensson and Taghavianfar (2020) and several other authors. Big Data is data characterised by high volume, high velocity and high variety (Austin and Kusumoto, 2016). Many terms have been used to refer to the use of data in organisational decision making. In this study we adopted data driven decision making (DDDM) as the process of using data in decision making while data driven organisation (DDO) refers to the organisation that makes use of DDDM. We drew inspiration from authors such as Treder (2019), Berntsson Svensson and Taghavianfar (2020) and Müller, Fay and vom Brocke (2018) who used DDDM and DDO in their studies.

The transformation to become data driven has been cited as a challenge with a few organisations successfully reaching their target despite investing resources (Berndtsson et al., 2020). This is the motivation of our study and becoming data driven starts by adopting and implementing technology such as data driven decision support system (Power, 2008). To explain technology adoption and implementation, a model for IT implementation developed by Zmud and Apple in 1989 was used. The model provides a six-stage process including initiation, adoption, adaptation, acceptance, routinisation, and infusion (Cooper & Zmud, 1990). When an organisation is implementing a technology, there is need to go through all the six stages successfully to deliver the intended benefits. The implementation model demonstrates that technology adoption goes beyond the decision to adopt and the delivery of the technology as several other steps are required to gain maximum benefits.

There are several factors that influence adoption and implementation of technology including the adoption and implementation data driven technology. Tornatzky and Fleischer (1990 cited in Entzenberg & Entzenberg, 2020, p.14) categorised the factors into Technological, Organisational and Environmental using their TOE framework. Realising a lot of focus has been put on technological and environmental factors, our study focused on organisational factors in the adoption and implementation of data driven decision making (DDDM). Alshawi, Missi and Irani (2011) defined organisational factors as factors linked to the structural, operational, human, and managerial aspect of the organisation. From the literature, we identified management support, availability of skills, organisational structure and processes, organisation size, organisational culture and change management as organisational factors that are influential in the adoption and implementation of DDDM.

Finally, themes and concepts captured in the literature review are summarised in Table 2.1 under thematic overview. The relevant literature is shown alongside each theme and concept.

2.5.1 Thematic Overview

Table 2.1 below shows an overview of themes, concepts and literature of this paper which gives a basis for interview guide shown in Appendix A.

Table 2.1: Thematic Overview

Theme	Concepts	Literature
Organisational Decision Making	Operational decision making Strategic decision making	Kulkarni et al., 2015; Shollo & Galliers, 2016; Laudon and Laudon 2002; Taylor & Purchase, 2016
Big Data and Big Data Analytics	Big Data Analytics	Lash & Zhao, 2016; Loya & Carden, 2017;

		Sivarajah et al., 2017
Organisational Factors	Management support	Berntsson Svensson and Taghavianfar, 2020; Treder, 2019; Mehrtens, Cragg & Mills, 2001; Cooper and Zmud, 1990; Iacovou, Benbasat and Dexter, 1995;
	Organisation Structure and Processes	Berntsson Svensson & Taghavianfar, 2020; Kumaresan & Liberona, 2018; Del Aguila-Obra & Padilla-Meléndez, 2006; DeCanio, Dibble & Amir-Atefi, 2000;
	Availability of skills	Berntsson Svensson and Taghavianfar, 2020; Grover et al., 2018; Kumaresan & Liberona, 2018; Svensson, Feldt & Torkar, 2019; Mehrtens, Cragg & Mills, 2001; Fink, 1998;
	Organisation Size	Garrison, 2009; Yao et al. 2003; DeTienne and Koberg 2002; Yeaple, 1992;
	Organisational culture	Kumaresan & Liberona, 2018; Berntsson Svensson & Taghavianfar, 2020; Treder, 2019; Fink 1998; Chatman and Jehn 1994;
	Change Management	Mikalef et al., 2018; Berntsson Svensson & Taghavianfar, 2020; Treder, 2019

3 Research Methodology

3.1 Research Strategy

This study aimed to answer the research question, "what organisational factors are influential in the adoption and implementation of data-driven decision-making (DDDM)?" by relying on the knowledge and perceptions of consultants and decision makers involved in implementing data driven decision systems. For this reason, we chose to use qualitative research. Loya and Carden (2017), highlights that a qualitative research can help uncover social, cultural, or political aspects of a phenomenon and is best suited for studies that aims to understand people's interpretation of a phenomenon in a real-life context. Also, we found qualitative method to be a perfect fit for this research since the research aimed to understand people's opinions and experiences in the area of data driven decision making. We aimed to use these opinions and experiences to identify and describe organizational factors that are influential in the implementation of data driven decision making.

Also, based on our research question, we decided to adopt a descriptive research type instead of either exploratory or explanatory. Bhattacherjee (2012, p.6) highlights that "descriptive research examines what, where, and when of a phenomenon." Since our research question seeks to identify '*what*' factors influences the implementation of data driven decision management, we settled for qualitative descriptive approach.

The research was conducted within the interpretivist paradigm. We chose to conduct an interpretive research as it suited our topic and research aim. In interpretivism, the ontology is that "our knowledge of reality is a social construction by human actors" (Walsham, 1995, p.376). Also, epistemologically, interpretivism "seek to determine motives, meanings, reasons, and other subjective experiences that are time- and context-bound" (Hudson & Ozanne, 1988, p.511). Our goal was to gain an understanding of data driven decision making adoption by engaging consultants and decision makers who shared meaning and motives based in their experiences. Myers & Klein (2001) highlights that interpretivism aims to gain knowledge of reality through social constructions like language, tools, documents, and shared meanings. In our study, we used semi-structured interviews as a tool to gain knowledge from our interviewees.

3.2 Conducting Literature Review

Our literature review was based on Bhattacherjee (2012) three-fold purposes of literature review. First, we surveyed the current state of knowledge in data driven decision making and technology adoption. Second, we identified prominent authors, literature, theories, and findings on the subject. Third, we identified the knowledge gap in our research area. We started our literature review targeting a broad search area to gain an understating of existing research. Once we got a picture of the existing literature, we narrowed down to the most relevant topics of our research including organisational decision making, Big Data and Big Data Analytics as well as technology adoption and implementation. While conducting the search, we kept a clear record of keywords, keyword combinations and the databases searched as recommended by Randolph (2009).

To maintain high quality in our research, we targeted to use literature from top peer reviewed journals. These were accessed through Google Scholar search and Lund University library search engine LUBsearch. On LUBsearch we made use of the advanced search feature to target peer reviewed journals such as *MIS Quarterly*, *Decision Support Systems* and *Journal of Management Information Systems*. Some of the key words we used in our research are as follows:

- "Organisational decision making" OR "Decision making".
- "Data driven decisions" OR "Data driven decision making" OR "Data driven organisation".
- "Big Data" OR "Big Data Analytics".
- "Technology adoption" OR "Technology adoption".
- "Organisational factors" AND "Technology adoption" OR "Technology implementation".

From the literature, we identified patterns and themes, similarities and difference across papers and authors (Braun & Clarke, 2006). The results are presented in Table 2.1 in Chapter 2 under thematic overview section. Our goal was to draw a guide for our empirical study. We then completed our analysis by comparing, interpreting, and contrasting this research findings to other similar researchers' findings and themes as advised by (Braun & Clarke, 2006).

3.3 Data collection

3.3.1 Interviews

Interviews were found to be a perfect fit for this research as a data collection method for reasons which are: helping researchers of this study to better understand and explore this research topic's opinions and behaviours, helping them to explain the phenomenon of this study which are factors that are influential in the adoption and implementation of data driven decision making (DDDM). In addition, this research sought to describe and clarify people's experiential life in the context of DDDM implementation towards becoming data driven as suggested by Schultze and Avital (2011, p.9) that a qualitative interview-based research should be descriptive on how people experienced life "as it is lived, felt, undergone, made sense and accomplished by human beings". Moreover, a mixed method interview approach was used in this paper whereby all the three philosophical orientations or stances on interpretive interviewing were used as suggested by Schultze and Avital (2011). These include neopositivist (interview as an instrument) stance, romantic (interviews as conversation) stance and localist (interview as a window on social reality) stance. These stances were applied stage by stage using an interview guide. Hence, neopositivist stance was first used in the interview guide, helping researchers of this study to:

> assume that interviewees are competent truth tellers, and that they are able to identify and articulate interior (e.g., individual experiences, background, feelings and values) and exterior (e.g., social practices, norms and structures) facts that are relevant to the phenomenon of interest (Schultze & Avital, 2011, p.3).

The romantic stance was used in the second stage of the interview guide to help researchers ask questions in a conversational and engaging manner. This stance was used to set up a foundation on which follow-up questions were to be asked, targeting occasions where each interviewee had an encounter with any of the themes presented in this research. Lastly, the localist stance was used because it helped interviewees to share their personal experiences and opinions about the factors which have an impact in the implementation of data driven decision making, making an interview as a window on social reality. Overall, an interview guide was used as a way to guide researchers on how and when they should apply each stance as well as making sure that each theme presented in this paper was addressed. Thus, this justifies why a mixed approach was used with the help of an interview guide in this paper.

Semi-structured Interviews

Semi-structured interviews were used to identify perceived organisational factors that influence the adoption and implementation of data driven decision making. Unlike structured and unstructured interviews whereby structured interviews use a strict script, targeting to strictly ask the exact same questions to all participants leading to close-ended questions which will not help to answer the research question, while unstructured interviews lead to a broad scope of conversations which might be difficult to identify factors (Bhattacherjee, 2012). Hence, semi-structured interviews were a perfect fit for this research since they are a balance of the two structured and unstructured interviews, leading to open-ended questions (Bhattacherjee, 2012). Moreover, because of its open-ended nature, semi-structured interviews were the most appropriate technique to discuss topics and obtain reasons for answers from interviewees (Recker, 2013). In addition to that, semi-structured interviews were considered best for this research as they are known to generate deeply contextual and authentic accounts of interviewees' experiences and their opinions on how they interpret them (Recker, 2013). Thus, semi-structured interviews were considered the right interview technique to use in this research since they had full potential to lead us towards answers of this research.

3.3.2 Selection of interviewees

To collect data, seven participants were selected from Swedish organisations. Two of them were decision makers in their respective organisations. These were selected as the users of data driven decision making systems. The other five were data analytics consultants helping their clients from different industries with the implementation of data driven technologies. Overall, we selected participants who play a key role in the adoption and implementation of data driven technologies both as technical implementers and users. Consultants in data driven technologies and decision makers were a selected group for this research because it was easier for them to provide an understanding of how organizational factors are influential in the implementation of DDDM. In addition to that, according to Patton (2014) interviewing people with knowledge and experience in the field of study is also encouraged when seeking to understand meanings from a phenomena. Thus, consultants were our first priority group of selection since they work with clients in different industries and different sizes of organisations. Therefore, beyond their technical knowledge, we stood to benefit true meanings on the factors which are influential towards becoming data driven from their experiences working with different organisations. This helped in collecting relevant data for this research as we did not need to look for interviewees from every industry and various sizes of organisations. Table *3.1* shows a summary with detailed information about this interviewees' role, expertise and the duration of interviews.

Table 3.1: Interview participant summary

Interviewee	Role	Industry	Experience
R1	BI Consultant (former Revenue Assurance Manager)	IT Consultancy	15
R2	Chief Finance Officer (CFO)	Manufacturing and Retail	20 23
R3	Principal Consultant Data Analytics	IT Consultancy	20
R4	Project Manager – Data Analytics	IT Consultancy	13
R5	Project Manager	Manufacturing	6
R6	User Experience Researcher Data Analytics	IT Consultancy	15
R7	Business Intelligence Developer	IT Consultancy in Banking	7

3.3.3 Conducting Interviews

Themes that originated from the literature review were used to generate interview questions. Based on these questions, a pilot study was conducted whereby six Information Systems students from Lund University were used as participants. A pilot study was done to make sure that final interview questions of this research were clear, easy to understand and could lead us to answers of this research. Moreover, as suggested by Myers & Newman (2007), the main aim of conducting a pilot study is to test the appropriateness of interview questions and give the researcher some early feedback on the research's viability. From the pilot study, interview questions were finalised and were used to structure an interview guide.

By using an interview guide shown in appendix A, a mixed approach was used as an interview strategy as suggested by Patton (2014) whereby all interviews in this research were conducted based on the three basic types of interview stances, which are neopositivist (interview as an instrument), romantic (interview as conversation) and localist (interview as a window on social reality). This means a neopositivist stance was first applied to start an interview by introducing the topic of this study to an interviewee, ensuring their confidentiality and asking for their permission to record the interview. The romantic stance was then applied in the second stage of interviews whereby an engaging conversation was done to understand experiences from each interviewee's role. This involved their duties in the organisations which they represented. After each interviewees' explanation of their duties and background, followed up questions related to this research's themes were asked. This was repeated on each interview by using an interview guide which also helped researchers of this study to target each theme represented in the literature section of this paper. By asking open-ended questions, each interviewee was then asked to reflect on their experiences and opinions about the discussed themes in the last section of the interview guide where a localist stance was used as a window on social reality. Overall, all interviews were conducted through Zoom, a video conference platform because most of the interviewees were working remotely due to the Covid-19 pandemic. Below is a five-stage interview process which was used to conduct interviews in this research.

- Introduction, both interviewees and interviewers introduced themselves (neopositivist stance).
- An explanation of the goals of the interview (neopositivist stance).
- Each interviewee was assured about the ethical issues, this includes their right to withdraw anytime during the interview (neopositivist).
- Permission to record each interview (neopositivist stance).
- Warm-up, a non-threatening conversational question asking each interviewee's background and duties in their organisations (romantic stance).
- Main body followed up questions connecting each participant's answer and themes of this research.
- Closure, thanking each interviewee for taking their time to participate and give a signal to end the interview.

Table 3.2 shows the date and time at which each interview was conducted as well as the duration of the interview.

Table 3.2. Interview date, time and duration

Interviewee	Interview Date, Time	Duration (minutes)
R1	23 April 2021, 10:00	40
R2	29 April 2021, 13:00	35
R3	29 April 2021, 14:00	42
R4	30 April 2021, 10:00	30
R5	3 May 2021, 10:00	24
R6	10 May 2021, 14:00	35
R7	11 May 2021, 16:00	43

3.4 Data Analysis Techniques

3.4.1 Transcribing

Raw data of interviews, according to Patton (2014) is the price desired by the qualitative inquirer, and nothing can replace it. Hence, all recorded interviews were transcribed in written form. However, to realize more value from the raw data, transcribing was done in close connection to the interviews. Moreover, since all interviews were conducted in English, transcribing was done with the help of Microsoft Word feature buy uploading an audio. An index was used on each of the rows in the transcripts for easy identification of specifics used in the empirical results and discussion. To avoid bias during transcribing, proofreading was done by the other researcher while listening to the corresponding recorded interview to make sure all raw data was transcribed correctly. This was repeated twice to make sure that the transcripts are accurate. All transcripts can be found in the Appendix B, C, D, E, F, G and H.

3.4.2 Coding

Coding was used to minimize the qualitative data to usable knowledge as suggested by Recker (2013). Coding is often used to organize data around principles, themes, or key ideas that have been found in the data. Table 3.3 shows the codes used for data analysis.

Table 3.3. Codes for data analysis

Codes	Concept	Theme
BDA	Big Data Analytics	Big Data
SDM	Strategic Decision Making	Organisational Decision Making
ODM	Operational Decision Making	Organisational Decision Making
MS	Management Support	Organisational Factors
OSP	Organisation Structure and Processes	Organisational Factors
AS	Availability of Skills	Organisational Factors
OS	Organisation Size	Organisational Factors
OC	Organisational culture	Organisational Factors
CM	Change Management	Organisational Factors

3.5 Research Quality and Ethics

In our study, we were determined to accomplish high research quality as well as considering research ethics. Hence, one way of expressing research quality in this paper was to maintain high credibility, transferability, validity and consistency throughout the whole research process. This was done by using the seven principles for interpretive field research as suggested by Klein and Myers (1999). These principles are the fundamental principle of the hermeneutic circle, contextualization, the interaction between the researcher and subject, abstraction and generalization, dialogical reasoning, multiple interpretations, and suspicion. Hence, the application of each principle will be explained on how it was used to improve this research's quality. In addition, we explain how research quality and ethics were maintained throughout the research including in literature review, data collection and data analysis sections.

The fundamental principle of the hermeneutic circle was used to constantly iterate by first looking at the big picture of our study, to the purpose of our study and down to more specific organisational factors that influence the implementation of data driven decision making as suggested by Klein and Myers (1999). This allowed a better understanding between the participants of this study and the researchers. Hence, the fundamental principle of hermeneutic circle was applied throughout the entire research process to ensure consistency, leading to high research quality.

The principle of contextualization helped to ensure the validity of this research. Literature review was used to get a detailed background on data driven decision making (DDDM) to comprehend the current affairs regarding influential organizational factors that could affect the implementation of DDDM. As supported by Klein and Myers (1999), this helped to guide researchers of this study to get a clear picture and idea on the events which led to the current topic of this study. Moreover, this principle helped this research to be more credible by giving a historical background on each construct based on the existing literature.

The principle of the interaction between the researcher and subject was used to ensure that participants' ethical considerations were observed. This includes informing participant's right to withdraw during the interview whenever they feel discomfort, letting them know that their personal and organisation's details will be anonymized, background and aim of this research and the freedom to choose any place of their choice to conduct the interview as it was done remotely. This was done through questioning between researchers and participants on how the data was going to be collected as Klein and Myers (1999) suggested.

The principle of abstraction and generalization was applied to make sure that findings of this research are transferable. This was achieved by comparing, interpreting and contrasting this research's finding to other similar research findings to generate themes as advised by Klein and Myers (1999). Inferences of this study were also analysed and compared with literature review performed in this study.

The principle of dialogical reasoning helped researchers in this study in comparing their initial thoughts or biases prior to performing the study to their actual results and attempting to spot inconsistencies through continuous revision. After each interview, researchers of this study discussed the responses of each participant then compared them to researchers' initial thoughts. As Klein and Myers (1999) suggested, this principle was constantly applied throughout the data collection process to ensure research quality.

The principle of multiple interpretations was used to comprehend a critical examination of potential differences in interpretations among participants who are saying the same thing but in different ways. According to Klein and Myers (1999), this principle calls for sensitivity to potential variations in interpretations between participants since people see the same occurrence through different lenses. Considering that all participants of this research were from different backgrounds, cultures, age groups and work experiences, the principle of multiple interpretations was used throughout the interviews and after.

The principle of suspicion helped to make sure that possible prejudices were taken into account for narratives provided by the participants. In addition to that, the principle helped researchers of this study to be very cautious for potential biases that might come from the participants Klein and Myers (1999). Any distortions from participant's answers were filtered out during the coding of each participant's transcript. This process was carefully done through researcher triangulation whereby one researcher could transcribe and the other researcher follows up on the same transcript for coding. This was repeated on each transcript to maintain consistency as well as avoiding bias.

3.5.1 Research Quality and Ethics in Literature Review.

In this research, relevant keywords or constructs were identified before beginning a search for literature. These keywords or constructs helped conductors of this research find more relevant literature for the research topic. Throughout the study, the use of these keywords was emphasized, allowing for valid conclusion drawings. The principle of contextualisation which was suggested by Klein and Myers (1999) was used to address the historical context of each keyword such as data driven organisation and data driven decision making and other constructs to ensure that the reader understands where those constructs and meanings came from before going into depth about the current state of research in the literature review. This led to this research's credibility as stated by Bhattacherjee (2012) that for a research to be credible, it must be perceived as believable by the readers. However, as mentioned by Timmins and McCabe (2005) a potential risk of using this approach is that the use of incorrect keywords can lower the quality of literature review. To make sure that this risk was eliminated, the use of high reputable research journals in Information Systems (IS) such as MIS Quarterly, Journal of Management Information Systems and European Journal of Information Systems and others was maintained throughout the literature research. Hence, this research's validity is determined by the quality of the references used. This was done to make sure that the research was credible, dependable, transferable, authentic and confirmable of literature by checking to see if all the literature being used was peer-reviewed.

3.5.2 Research Quality and Ethics in Data Collection.

When participants of this research were selected, each participant was given a document with a summary of the research aim and topic including the information on how the interviews were to be conducted. Furthermore, the fact that participation in this study was voluntary was clarified, implying that interviewees were free to choose whether or not to participate, with no negative consequences (Bhattacherjee, 2012; Recker, 2013). The same information was given to all interviewees since they were given similar sheets. Furthermore, before the data was collected, the interviewees were given disclosure, which is the provision of information about the research to potential interviewees with the option of withdrawing their participation based on our thesis objectives and general themes of the questionnaire. According to Bhattacherjee (2012), it is important to inform interviewees about the researchers and the study's objectives. Additionally, prior to the interview, the interviewees were given a brief interview guide containing some of the more general questions to help them understand the study's aim.

In addition to that, the principle of multiple interpretations was applied during data collection. The use of this principle helped to examine potential variations in interpreting participant's answers. This was done to avoid bias in interpreting what the participants were saying as data was being collected.

3.5.3 Research Quality and Ethics in Data Analysis.

A research plan, data collection methods, data analysis techniques, decisions made, and the end results were all documented to create a clear audit trail of this research. Moreover, peer reviews by colleagues who were not directly involved in the research were conducted to ensure dependability of research leading to high quality. In these peer reviews, the reviewer verified that the findings and conclusions were supported by the empirical data gathered.

By using the principle of suspicion, the peer reviews also served as independent audit to the research process and decisions which were made. By doing so, this supports a true definition of research dependability by Lincoln and Guba (1982) that research findings should be repeatable and consistent. In addition to that, researcher triangulation was used to ensure consistency. Since this research was conducted by two researchers, researcher triangulation was found to be a good practice as a way of minimizing bias. This is so because researcher triangulation is known to be a method of checking or verifying conclusions by removing methodological flaws, as well as investigating data bias (Kim & Chan, 2014). When data was collected for this research, researcher triangulation was used in a way that one person could transcribe while the other checked the transcription against the corresponding interview audio to see if it was accurate. To ensure that bias was removed, this procedure was replicated several times during the entire data transcription process, thus, ensuring research quality.

4 Empirical Results

In this chapter we present our findings from the interviews conducted with seven interviewees R1, R2, R3, R4, R5, R6 and R7. These interviewees were all from organisations operation in Sweden. We first look at the nature of decisions targeted by organisations based on our participants' experience either as consultants or decision makers. We also look at the significance of Big Data and Big Data Analytics in the adoption of data driven decision making. Finally, we present the organisational factors identified through the interviews.

To present our empirical results, we numbered the rows in the interview transcripts shown in Appendix B to H. For example, R1:5 or R1 (5) refers to a response given by R1 on row number 5 in the transcript. Also, (R1:5, 15, 17) indicates R1 responses in rows 5, 15 and 17 respectively. This was done to ensure easy reference between empirical results and the interview transcripts.

4.1 Organisational Decision Making

Table 4.1 below shows the rows in which the codes appear in the interview transcripts. For example, R1 spoke about strategic decision making (code SDM) on rows 5, 15 and 17. This table highlights the frequency at which each interviewee talked about a specific code giving insights into how they view the importance of each factor or concept in the implementation of data driven decision making.

Table 4.1: Overview of transcribed data under Organisational Decision-Making theme

Theme	Factor	Code	R1	R2	R3	R4	R5	R6	R7
Organisational Decision Making	Strategic Decision Making	SDM	5; 15; 17;	9; 33	18; 20	36;	9, 11	9	9; 27
	Operational Decision Making	ODM	5; 15; 17;	7; 9; 33	18; 20	36;	9, 11	9	9, 27

When asked about the type of decisions they sought to support using data, all the interviewees highlighted that their organisations or their clients aimed to support decisions at all levels from operational to strategic decisions. R2 (9) highlighted that they primarily target to use data for their day-to-day decisions but also made some important strategic decisions using the data. While operational decisions rely on short-term trends like daily trends, strategic decisions rely on long-term trends showing the bigger picture (R2:33). R3 (18) indicated that their clients target strategic decisions as the end goal, but these strategic decisions are a combination of operational decisions so the two are interlinked. This view was supported by R1 (15) who indicated that they used data in both short-term and long-term decision, from predicting today's operations to forecasting budgets and company strategy. In an environment with ERP systems, operational decisions can be easily supported due to well defined operational steps (R3:20). On the other hand, when implementing data driven strategic decisions, smaller user groups are usually involved thus simplifying the process of understanding their needs and this improves the chances of success (R3:18). This is because strategic decisions are usually made by high level management (R5:9). The idea that strategic decisions are usually the focus of top management was further cemented by R7 (9) who said, "*higher management … would want to see how each department is working at a bird's eye view to strategize everything*". At low level, functional teams are more focused on day-to-day data like product performance per region (R7:9). While data can be used to drive both operational and strategic decision making, some organisations may choose to focus on becoming data driven in one of the two, either operational or both (R6:9). In addition to operational and strategic decisions, R5 (9) used data to support project decisions as well. Strategic decisions require both the use of historical data and the decision maker's intuition. Therefore, strategic decision makers should always seek to question both their gut feeling and data until there is a consensus on the course of action (R4:36).

4.2 Big Data and Big Data Analytics

Table 4.2 shows the rows in which the BDA code appear in the interview transcripts. This table highlights the frequency at which each interviewee talks about a specific code giving insights into how they view the importance of each factor or concept in the implementation of data driven decision making. For example, Big Data and Big Data Analytics (code BDA) were mentioned 10 times throughout the seven interviews.

Table 4.2: Overview of transcribed data under Big Data theme

Theme	Factor	Code	R1	R2	R3	R4	R5	R6	R7
Big Data	Big Data Analytics	BDA	2; 25	11; 35;	28;	48; 50	25	11	13

On the importance of Big Data in data driven decision making, our interviewees considered it very important but not mandatory (R2:11; R1:25; R3:28; R4:48, 50; R6:11). The view that an organisation can start its transformation to become data driven with less data and grow with time was shared among interviewees (R2:11; R1:25; R3:28; R4;50). R2 (11) also highlighted that part of their organisation used Big Data while the other sections relied on smaller volumes of data but were still data driven. R3 (28) and R6 (11) also suggested that bigger companies might need Big Data more than smaller companies when implementing data driven decision making. R7 (13) emphasised the importance of having high quality data over large volumes of data. Whatever volume of data an organisation has, it needs to be of good quality (R7:13). Overall, an organisation "*… needs some sort of data to be data driven*" (R6:11).

4.3 Organisational Factors

Table 4.3 shows the rows in which each factor (code) appears in the interview transcripts. This table highlights the frequency at which each interviewee talks about a specific code giving insights into how they view the importance of each factor or concept in the implementation of data driven decision making. For example, organisational structure and processes factor (code OSP) was mentioned more than 30 times throughout the seven interviews showing how significant the interviewees thought it was when adopting and implementing data driven decision making.

Table 4.3: Overview of transcribed data under Organisational Factors theme

Theme	Factor	Code	R1	R2	R3	R4	R5	R6	R7
Organisational Factors	Management Support	MS	7;	27; 29; 39	6; 8;	12;	21; 23	17; 26	9; 21
	Organisational Structure and Processes	OSP	7; 9; 21; 23;	13; 19; 41; 43;	6; 8; 12; 14; 22; 26; 28;	10; 22; 24; 38; 40;	13; 15; 17; 23	13; 15; 19; 25	17; 19; 23
	Availability of skills	AS	5; 13; 27;	31;	4; 22;	4; 6; 14; 22; 40; 52;	25; 27	13; 15; 25	11; 15; 23; 25; 29; 35
	Organisational Size	OS	9;	19; 41;	6; 9; 13		31	6; 11	
	Organisational Culture	OC	5; 19;	25; 27;	4; 6; 16; 24; 32;	16;	19	19; 21	15; 17; 23; 25; 29
	Change Management	CM	9; 21;	37;	24		29	23; 25	21; 29; 31
Newly Identified Factors and Codes	Industry or Sector	IS		7;11	28	4			11
	Perceived Value	PV				4		13; 25	13; 15; 35

4.3.1 Management support

All the interviewees highlighted the importance of management support in their organisations when implementing data driven decision making. According to the results, we observed that there was high frequency for the need of management support in their organisation (R2:27, 29, 39). R2 mentions that their organisation is still growing, hence, it is essential for the management team to support the implementation of any technology. This was also highlighted by R1 (7) who said, *"it is very important for the management to really be always a step ahead of the team so that they can support them"*. Without the management support, it is a huddle to successfully implement data driven decision making (R1:7). This is because the management team is the one that makes decisions on the implementation of technologies in their organisations, therefore, it was found necessary as stated by R3 (6, 8) that for the implementation of data driven decision making to be successful, the management team buy-in is required. Moreover, R4 (12) also emphasised on the need for management support since they are the ones who make organisational decisions. As a result, organizations can achieve better outcomes if the management team make choices that create an atmosphere conducive for effective execution. The interviewee R4 (12) mentioned that in their organisation, the management team was considered to be also in the implementation team. This is so because they think, for the management team to more supportive, they need to be part of the implementation process so that they can understand the kind of support required for a successful implementation. This is also a situation shared by R3 (6) that most of the management teams in some organisations do not understand the implications of implementing data driven decision making resulting in less management support which leads to implementation failure. R7 raised a point that, for managers to support the implementation of data driven decision making in their organisations, it is crucial that they understand their organisational objective. Overall, for organisations to be successful when implementing their technologies, the management team needs to be part of the implementation team for them to be aware of the implementation needs so that they can make decisions which supports and provides those needs as stated by R5 (23), *"we work with our management as a team and this has helped a lot in progressing together as everyone's input has a factor in our outcomes"*.

4.3.2 Organisational Structure and Processes

Organisational structure and processes were identified as a key factor when implementing data driven decision making (R2:19; R1:9; R3:8; R4:10; R5:13). The impact that the organisational structure will have on the implementation of data driven initiatives will depend on the size of the organisation, for example, R1 and R2's organisation did not have to adjust their structure because the organisations were small in size (R2:19; R1:9). On the other hand, R5 (13, 15) attributes their success in implementing data driven decisions to the fact that they have had to keep adjusting the way they work, and they have done that successfully. "*We have had to keep adjusting our ways to keep improving*" (R5:13). R6 (19) believes transforming the organisation's processes to match data driven way of making decision is an important step. With their organisation rapidly expanding through acquiring new companies, R7 (19) need to manoeuvre through complex and changing organisational structure and processes. Despite the complex structure of the organisation, it is important to have a consolidated view of the data to make effective decisions (R7:19).

Whether an organisation is horizontal or flat in its structure was highlighted as a factor and to some extent a risk to the success of the implementation (R3:8). R3 argued that in a vertical organisation, having management that is resistant to change could act as a blocker to the adoption and implementation of data driven culture. R5 (23) believes the lack of hierarchy in their organisations has helped significantly in implementing data driven decisions as everyone has a platform to contribute with ideas. In addition, the organisation's processes determine the quality of data captured which in turn affects the quality of decisions made from the data (R7:17). "*If there is no clear process for them on how to update the data, then we will get a lot of empty values or incorrect values inconsistencies in the values that they input*" (R7:17). R4 (10) shared a similar view that the processes used by the organisation also determine the type of data that can be gathered and analysed for decision making purposes, hence there might be need to tweak or adjust organisational processes to align with the data driven culture requirements. Referring to the process of implementing data driven decision making, R6 (25) said "*there needs to be a clear idea about how that ties into different processes that are going to support people in using these different techniques.*"

The question on who is accountable for data driven decisions drew some diverging opinions from the interviewees. According to R2 (21), the decision maker still has to apply their intelligence and reasoning to the data so they remain accountable for every decision made. R3 (14) disagreed with this view by stating that "*... if you have a decision support system of any kind, it is always the fault of the system if something goes wrong*". However, R3 (14) explained further that it is the responsibility of system owners to point the actual source of the problem, otherwise all the problems will be attributed to the system. R5 (17) highlights that unless the decisions are automated, the human decision makers retain the accountability of decisions made even if they are data driven.

4.3.3 Availability of skills

The empirical results show that the availability of skills is an essential factor during the implementation of data driven decision making. It was noted that without skilled employees, chances are high that the implementation would be a failure. As highlighted by R2 (31), the management team needs to make sure that they have hired skilled team members with the required expertise for successful implementation of data driven decision making. R1 (5, 13, 21) shared the same view but emphasizing that for successful implementation, team members need to know the type of data which needs to be used, the type of tools and the implementation objective. In addition to that, according to R3 (22), "*if you want to become data driven, truly data driven, you must have the skills of working with the data and the tools as well"*. The use of competent business intelligence analysts, program analysts and business analysts can be very useful as a way to maximise success. R4 (22) also mentions that, *"you need to have some basic training so you can read diagrams and charts and understand some basic concepts"*. In addition to that, R7 emphasised that the availability of skilled team members is influential in the implementation of data driven decision making. R5 said that in their organisation they cannot operate without team members who have the competence to bring insights from data by using their analytical skills. Companies must train their employees to become data literate so that they have the skills to change data into meaningful insights (R6: 13, 15, 25).

4.3.4 Organisation Size

Organisation size was identified as an influential factor by our interviewees. The interviewees did not consider organisation size as either an enabler or inhibitor, but they considered it as a factor that can influence the implementation approach of an organisation (R2: 43; R1: 9,11; R3:28; R6:11). For example, R2 (43) highlighted how small companies can have the flexibility to do trial and error until they get it right. On the other hand, big organisations are compelled to have departments specialising on providing data resources for the users (R2:43). Organisation size was also closely linked to the organisational structure and processes. When implementing data driven systems, small organisations do not necessarily need to significantly change their structure or processes (R2:19; R1:9). On the other hand, larger organisations need to adjust their organisational structure or processes to accommodate the new way of decision making. R3 (28) indicated that while Big Data is not a requirement for small organisations, it might be a mandatory requirement for large organisations that might need to have separate departments to handle data. "*When you look at big companies, they have serious amounts of data in data warehouses which requires a lot of transformation, that is Big Data. On the other hand, smaller companies have less amount of data in some cases excel sheets.*" (R6:11).

However, R7 (35) strongly believes that as long the quality of the data is good enough, it does not matter whether an organisation is small or large.

4.3.5 Organisational culture

What was clarified during the empirical investigation is that members or employees of an organisations needs to embrace the data driven decision making approach for the organisation to successfully become data driven. All the interviewees of this research confirmed that it is crucial for team members to be at the same level of understanding the use of data for decision making in their organizations. R2 (25, 27) highlights that it is important for team members to appreciate and accept the use of data for decision making in their organization as it makes the implementation easier and successful. The need for organizational culture was also mentioned by R1 (5, 19) as there was more emphasis on on-boarding which means members in an organization need to be supportive and embracive when an organization decides to implement data driven decision making. R3 (6) also emphasised that by saying "*I think it's critical for leaders at all levels to make sure that they train their employees to always bring data which supports decisions, that will also help by making sure every employee appreciates the use of data to make decisions".* Moreover, in support of organizational culture, R5 (19) shared how they ensure it at their company by saying, *"we try as an organisation to ensure that everyone is on board before we start any projects so that we build the culture amongst employees".* Thus, R4 (16) points out that organizational culture can be considered to be very influential in the implementation of data driven decision making in organisations. R6 also highlighted that organisational culture is a factor which depends on the type of industry or sector the organisation operates in. For a food industry organisation, it might not be necessary for every employee to know or be bothered with what members in the IT department are doing (R7).

4.3.6 Change Management

During the interviews, it was clear that change is inevitable when implementing data driven decision making. The size of the project being implemented determines the amount of effort required on change management activities (R2:37). Some changes might require small change management measures like emails or memos, while some would require workshops and roadshows to raise awareness of the change (R2:37). Change management is a tool used to ensure no employee is left behind as the organisation transforms into data driven. In R1's organisation, change management was delegated to various departments supported by a centralised team which coordinated the activities (R1:19, 21). R3 (24) acknowledged the importance of change management in the implementation of data analytics projects and indicated the need for specialised change management skills. "*Change management is one of those parts that you do, but you don't do it like a change management consultant because you're not skilled enough for that.*" (R3:24). R3 (24) highlighted that implementing new systems in organisations involves changing the ways in which the organisation works hence the need to proper change management handled by a Change Management Consultant. R6 (23) also supported the need to have qualified change management people handling the organisation's change management due to the importance of the process. According to R5 (29) change is a challenge that needs to be handled properly to succeed. "*Adjusting the way you work and the people you work with takes time.*" (R5:29). Whenever there is change, be it a new system or adjustment, there is need to navigate resistance to change by users (R7:31). From the empirical results, change management is an important factor that if not handled properly, it can negatively affect the value delivered by the adoption and implementation process.

4.3.7 Organisation Sector or Industry

While conducting interviews, it became clear that the sector or industry in which the organisation belongs affects the adoption and implementation of data driven decision making. R4 (4) emphasised the need for implementers to understand their data which differ depending on the company. Quoting R4 (4), implementation process *"... includes knowing what your data is, and this is different for different companies and the type of company matters too"*. Responding to whether Big Data is a requirement for implementing data driven decision making, R3 (28) said "*in some industries they need to use huge amounts of data to get value and some organisations can still be considered data driven by using small amount of data since they just use it to make simple decisions"*. R3's view shows that the meaning of being data driven depends on the industry the organisation belongs to. This was evident in R5's interview. Based on R5's manufacturing industry experience as a Project Manager, the definition of being data driven was centred around referencing historical data in whatever form to make decisions on the next steps. On the other hand, R3 repeatedly brought up the use of sophisticated ERP systems as a source of data.

4.3.8 Perceived Value of Adoption

During the interviews, R4 (4) emphasised the need for an organisation to be clear on what value they need to deliver through data driven decision making. When asked about what influences organisations' adoption and implementation of data driven decision making, R4 (4) said, "*you need to really understand what your company wants to achieve by using data*". This was supported by R6 (13) who argued that thinking about the value the technology is set to deliver is more beneficial than thinking about the technology itself. The value can be in form of improved efficiency, market growth or improved customer satisfaction (R6:13). While other interviewees did not directly bring up this factor, we noted it was always the factor behind management support. If management perceive data driven decision making to be beneficial to the organisation, they will likely support the decision to adopt. Not only will they support the decision, but they will also avail the required resources for the implementation to be successful.

4.4 Empirical Results Summary

Table 4.4 shows the summary of the factors identified during the interview process. We identified eight organisational factors including management support, organisational structure and processes, availability of skills, organisation size, organisational culture and change management. Two of the nine factors are new as we had not identified these in the literature review. These are organisation industry or sector and perceived value. Organisational decision making and BDA were also identified as concepts that are important in the data driven decision making implementation.

Table 4.4. Empirical results summary table

Factor/Concept	Summary
Organisational Decision Making	The results from the interviews showed that organisations aim to support both operational and strategic decisions using their data. The interviewees indicated that all type of decisions can be data driven. Operational decisions make use of short-term data trends

	like hourly, daily, weekly, and so on. On the other hand, strategic decisions can be driven by long term trend like quarterly, bi-annually, annually, or even longer.
Big Data Analytics	Big Data Analytics was identified as a key part of data driven decision making. However, it was noted that an organisation can become data driven with any amount of data not necessarily Big Data. Large organisations might need Big Data more than smaller organisations when implementing data driven decision making.
Management Support	Through interviews, the need for managers to support or make decisions which supports the implementation of data driven decision making was identified as an influential factor. However, for managers to be supportive, the results shows that it is important for them to understand the implementation needs.
Organisational Structure and Processes	The implementation of data driven decision making is hugely dependent on the organisation structure and processes. Depending on the size of the organisation, there might be need for restructuring and alignment of processes. Larger organisations often need to change their structure and processes while smaller companies might not change any. Also, organisation processes determine how the data is captured and affects the quality of the data. There might be need to adjust processes to improve data quality.
Availability of skills	Results from interviews show that availability of skills has an impact in the implementation of data driven decision making. The availability of employees with analytical expertise and competence was mentioned as one of the most influential factors towards becoming data driven. The importance of having employees who can read and understand data has a direct impact on how an organization will transition towards becoming data driven.
Organisation Size	The size of organisation was identified as factor that affects or determines the approach of implementation. Small organisations are agile and flexible. Large organisations are considered rigid but have more resources. The adoption and implementation of data driven decision making in large organisations can constitute a series of large-scale projects including data warehouses. On the other hand, small organisations implementation of data driven decision making can be in form of small-scale initiatives involving a few individuals.
Organisational culture	Organisational culture was identified in the interviews as an influential factor towards becoming data driven. Results shows that although organizational culture depends on industry and size of the organisation whereby some have departments dedicated for IT, it was still considered influential if everyone in an organization appreciates the use of data for decision making regardless of the department they belong in their organisations.
Change Management	The implementation of data driven decision making introduces a series of organisational changes. If not managed properly, this change can have detrimental effects to the performance of the organisation. As a result, change management is an important factor to successfully implement data driven decision making. This includes training employees, communicating changes properly and

	ensuring everyone in the organisation appreciate the value of the change. In some cases, it is advisable to make use of a change management professional.
Organisation Sector or Industry	When adopting and implementing data driven decision making, the sector or industry in which the organisation is operating matters. The industry determines the type of data that needs to be captured and fed into the decision-making process. Our interviewees pointed out that some industries require large volumes of data to become data driven, while some can make use of smaller volumes of data. Therefore, the industry will determine what it takes for an organisation to become data driven.
Perceived Value	When the value expected from adopting and implementing data driven decision making is high, management will support adoption and avail enough resources to support implementation. Our interviewees indicated that it is important for an implementing organisation to be clear on what value they seek to deliver. Once the value is known to both management and employees, it can serve as a motivator during implementation and result in success.

5 Discussion

In this chapter, we discuss the themes identified in literature alongside the results of our empirical research. We discuss both the similarities and differences between the existing literature and our empirical results. The identified themes are organisational decision making, Big Data and organisational factors in technology adoption. The organizational factors will be highlighted and discussed comparing observations from the literature review and results from interviews.

5.1 Organisational Decision Making

Before looking at the organisational factors, it was important that we drew an understanding of organisational decision making and what it meant to our interviewees. In our empirical research, our interviewees viewed organisational decision making as an important process that defines the current and future performance of the organisation. The value of using data to drive decisions was clear in both empirical results and literature. Authors such as Kim and Chan (2014) and Müller, Fay and vom Brocke (2018) highlighted how data can improve the quality of decisions and subsequently the organisations performance. All our interviewees agreed data can be used to improve all forms of decisions, be it strategic or operational decisions. The aim is to evaluate possible options and make the best choice as defined by Shollo and Galliers (2016). While data driven decision making could be applied to both operational and strategic decisions, there were few differences highlighted by the interviewees. Interviewees viewed operational decisions as short-term decisions that relies on short-term data trends. On the other hand, strategic decisions were viewed as long-term decisions which required longer data trends to support them. R3 looked at strategic decisions as a process reserved for high level management and its target users are fewer than those of operational decision making. Overall, there was a common understanding on what organisational decision-making entails, the advantages of being data-driven and the type of decisions that could be data driven.

5.2 Big Data and Big Data Analytics

Big Data and Big Data Analytics are concepts closely associated with data driven decision making in literature. Big Data is widely viewed as an enabler of data driven decision making by authors such as Berntsson Svensson and Taghavianfar (2020) and Treder (2019). However, when the interviewees were asked about the importance of Big Data in data driven decision making, they considered it important but not mandatory. The argument was that any form of data even without the volume, velocity and variety attributes of Big Data can be used in driving organisational decisions. R7 argued that the quality of the data is more important than other attributes like volume. R3 and R6 viewed Big Data as a necessity in large organisations while small organisations could make decisions based on small data sources like excel sheets. While we presented Big Data as a mandatory component of data driven decision making in literature review, we acknowledge the view from empirical research that any data can drive decisions. Organisations can start the implementation of data driven decision making with small amounts of data and scale up according to their needs.

5.3 Organisational Factors

In this section, we discuss the identified organisational factors that affect the implementation of data driven decision making. Hence, management support, organisational structure and processes, availability of skills, organisational size, organisational culture, and change management will be discussed based on literature and then supported by empirical results. Also, two additional factors which were only identified in interviews will be discussed as well. These are organisation sector or industry and perceived value of data driven decision making.

5.3.1 Management support

This research confirms with evidence shown in the empirical results and literature review that management support is indeed an influential factor in the implementation of data driven decision making (DDDM) in organisations. As supported by Treder (2019) in the literature review, organizations may effectively resolve obstacles and resistance during the implementation of DDDM with the help of management or executive support. This was also confirmed in the empirical results by R1, R2, R3, R4, R5, R6 and R7 agreeing that it is crucial for the management team to be supportive especially during the implementation of any technology in an organisation. Also, top management support is one of the factors that Cooper and Zmud (1990) described as the most influential factors that can have either a positive or negative impact in the implementation of DDDM. In addition, R2 emphasised the importance of having management support in their organisation. This confirms that management support is indeed an influential factor, and the employees performs better if they are being supported by management. This shows that employees or organisation members who play a role in the implementation stage mostly rely on the management team's decisions. If the management team does not share the same view with those in the implementation stage, chances are high that the organisation will fail to implement the technology (Mehrtens, Cragg & Mills, 2001). As a result, organizations can achieve better outcomes if the management team makes decisions that create an atmosphere conducive for effective execution.

Based on the empirical results and literature review, one can generalise that management support is a must for adopting and implementing any technology in an organisation. R1 also agrees with this view that the implementation of DDDM is actually a challenge if there is no controlled and constant management support in the adoption and implementation phases. According to this research, the management team is the one which ensures that there is a conducive environment in an organisation through supportive decisions which might have a direct impact on the implementation of DDDM. This can be done by making sure that the management team understands why they need to implement a certain technology, leading them to have a clear goal. By doing so, the management team can also get an opportunity to know and understand what is needed to reach to their goal. Once the needs are known, then it will be easy for the management team to make decisions that supports the implementation needs. The management team may help with the following: funds needed to get the type of data required for an organization to become a data driven, allowing the implementation team to share their views on what they think is essential for a successful implementation and also moral support. In the literature review, Mehrtens, Cragg and Mills (2001) share the same view that the top executives should at least be part of the implementation team for them to understand what the team needs and make decisions that provides them with a comfortable environment to work. This shows that both the literature review and the empirical results recognize the value of getting management support, as it was highlighted by R4 that management support has a huge impact on the implementation of DDDM in organizations.

5.3.2 Organisational Structure and Processes

The empirical results of this research agree with the literature on the impact of organisational structure and processes during implementation of data driven decision making (DDDM). All the interviewees agreed with Del Aguila-Obra and Padilla-Meléndez (2006) view that adoption of technology is dependent on organisational structure. The empirical results showed that implementing DDDM in flat organisations is considered easier when compared to hierarchical organisations. R3 highlighted in hierarchical organisations, the adoption of technology is much more dependent on management view, that is, if the manager is not willing to adopt DDDM, the company or department will not adopt. When compared to flat organisation structure, the decision is based on team views not individuals therefore chances of adoption are higher (R5).

Also, Berntsson Svensson and Taghavianfar (2020) highlighted the need for organisational alignment when becoming a DDO. This view is echoed by Kumaresan and Liberona (2018) who suggested changing the business structure as a way of introducing the data driven culture. While all our interviewees agreeded that there might be need for change of structure, they emphasised that it depends on the size of the organisation. The shared view was that small organisations do not necessarily need to adjust their structure. On the other hand, change of structure was considered critical for large organisations who might even need to introduce a dedicated team focusing on data and its use. Overall, failure to align organisational structure to the data driven culture was agreeably a key factor in implementing DDDM especially in large organisations with complex structure and processes.

The issue of accountability in data driven organisations is one area where there was no consensus in our empirical results. Only two of our interviewees agreed with Berntsson Svensson and Taghavianfar (2020) view that decision makers must not be accountable for their decisions in a DDO. The rest expressed the need for decision makers to apply their intelligence to the data therefore they argued that the manager must retain accountability. Where the accountability lies has the potential to influence the user's propensity to use or ignore the decision being conveyed by the data. Therefore, moving accountability away from decision makers as the organisation become more and more data driven is important as it can encourage people to trust data and systems involved.

5.3.3 Availability of skills

In the literature review section of this paper, it has been highlighted that availability of skills was classified as the most important factors that any organisation will need to consider for a successful adoption and implementation of any technology (Mehrtens, Cragg & Mills, 2001). This was also confirmed in empirical results by all interviewees as one of the most essential resources an organisation must have for successful implementation of data driven decision making (DDDM). This means it is crucial for an organisation to hire employees with necessary skills for a successful implementation. According to Svensson, Feldt and Torkar, (2019), organisations' readiness to implement any technology is determined by the level of IT awareness among both IT professionals and non-IT professionals. The ability of employees to interpret and draw insights for decision making is one of the skills that an organization needs to consider for it to become data driven (R1). When recruiting staff members to help with the implementation of DDDM, one of the qualities that a company can look for is analytical skills (Grover et al., 2018; Kumaresan & Liberona, 2018). Moreover, evidence from empirical results by R4, shows that it is also important that employees in an organisation are willing to relearn new technological skills which are required by an organization towards the implementation of DDDM. This was also supported by R5 stating that having analytical skills in their organization is mandatory since it improves the chances of successful implementation of DDDM.

Due to rapid technological advancements, it can be daunting for IT professional and non-professionals to keep up with the technological skills that are needed for new technologies that an organisation might want to implement. This has also contributed to the high failure rate in implementation of data driven decision making in organisations since some of their employees might not have the technical skills required to implement the new technology. Thus, R3 stressed that it is crucial for organisations to train their employees to make sure that they are equipped with necessary skills to implement DDDM. In addition, Svensson, Feldt and Torkar (2019) supports the same idea of training team members who are to participate in the implementation as well as making sure that everyone is onboard. R2 classifies availability of skills as a factor which is equally important to on-boarding of employees. An organisation cannot count on someone who does not understand the type of data needed, the aim and knowledge about the technological tools that are required in the implementation stage. This has been seen as one of the most common factors that affect how an organisation executes its IT projects and determines whether the execution or implementation will be a success or failure (R4).

Overall, based on the literature review and evidence from empirical results, one can consider availability of skills such as analytical skills and data literacy to be influential for the implementation of DDDM. According to R4, an organisation can fail to get the value from their investments towards becoming a data driven because of its employees’ lack competence or ability to turn data into meaningful insights that an organisation can use for DDDM.

5.3.4 Organisation Size

Two contradicting views are presented in literature. One that considers large organisations’ financial and human resources as an advantage in the adoption and implementation of new technologies such as data driven systems (Garrison, 2009; Yao et al. , 2003). On the other hand, others argue that small organisations’ flexibility and agility is a positive factor that makes it easier for smaller organisations to adopt new systems (DeTienne & Koberg, 2002; Yeaple, 1992). Our interviewees agreed with the second view that smaller organisations are agile while larger organisations are rigid. Some confirmed that they had benefited from the small size of their organisations during their implementation stage. R1, R2 and R3 argued that small organisations can skip complex steps like organisational and process changes during adoption and implementation. This simplifies the implementation process and increases the chances of success.

However, there is no evidence in both literature and our empirical results that associates higher failure rate with larger organisations or vice versa. Instead, there is an understanding that organisation size will likely determine the implementation approach when adopting DDDM. Due to rigid structure and complex processes, adopting and implementing new systems is a complex process in large organisations. However, large organisations have sufficient resources to manoeuvrer their way around the complexity (R3). Therefore, organisation size is indeed a factor in the adoption and implementation of DDDM but it is neither an enabler nor an inhibitor.

Instead, organisations only need to pick an implementation approach that suits their size. For example, R6 believes large organisations need to have Big Data as part of their implementation while smaller organisations can succeed with any form of data.

5.3.5 Organisational culture

In order to become data driven, both literature review and empirical results address the importance of having a data driven culture which embraces the use of data to make informed decisions. The transition to become data driven is often influenced by organizational culture (Chatman & Jehn, 1994). R1 explains culture as the willingness of employees or team members involved in the implementation of data driven decision making to use and embrace a new way of making decisions using data. This means how employees value the use of data to make decisions has an impact on whether an organisation will be successful or not during the implementation of the needed approach such as DDDM. From this paper's empirical results, it was clearly highlighted that organisation's culture has a significant impact on the implementation of DDDM (R3). According to Kumaresan and Liberona, (2018), if employees or members who participate in the implementation of DDDM are resistive to new technology change, it will be a challenge for an organisation to successfully implement a new way of making decisions using data since they will be prioritizing of preferring their old way of making decisions. R4 also supports that point but emphasizing on employees' reluctance to learn and appreciate the new way of making decisions. Despite the fact that automating decisions to be data driven makes employees' jobs easier, it is still a challenge for them to unlearn and relearn the new way of making decisions in their organisations (Treder, 2019).

Relying on both literature review and empirical results, organisational culture can be considered a threat in many organisations as it can be difficult to ensure that there is enough technological acceptance within the organisation to be able to implement DDDM as a new technology that can be used to inform decisions. However, R4 does not share the same point of view arguing that it depends on the type and size of an organisation. This means if an organisation is small, then on-boarding is easy but if the organisation is big, chances are high that the issue of culture will need to be factored in when implementing or introducing any new technology in an organisation. Although R4 had a different view from the majority of this research's interviewees, it is worth considering that organisational culture is a potential factor that can be influential in the implementation of DDDM but varying with the type and size of an organisation. R5 also mentioned that some organisations do not need to have everyone to understand what the IT team is working on since they will be probably working in different departments of the same organisation. Moreover, as mentioned by R6 and R7 it was highlighted that in other companies, only the management team will be part of decision making because of its size. This means in this case; it will be pointless for the whole organisation to be fully acquainted to data.

5.3.6 Change Management

The process of becoming data driven or adopting data driven decision making introduces significant change in an organisation from structure to processes. Both the workforce and leaders can be affected by fear of change (Treder, 2019). Therefore, both our empirical results and the literature recognised the importance of proper change management when adopting data driven decision making. Berntsson Svensson and Taghavianfar (2020) identified failure to manage change as a potential inhibitor to the data driven transformation process. All the interviewees acknowledged the need to manage change during the adoption process. However, the scale of the change management activities is dependent on the size or impact of the change. In R2's organisation, change management activities varied from roadshows and workshops to change notification e-mails. In some cases, change management requires change management experts as highlighted by R3 and R6 who in their organisation made use of change management consultants. Some organisations rely on decentralisation of change management activities to individual departments as in the case of R1's organisation. Overall, there is a recognition of the importance of managing change properly when adopting DDDM in order to gain maximum benefits.

5.3.7 Organisation Sector or Industry

In the literature review we did not identify the organisation's sector or industry as one of the organisational factors. However, the empirical results showed that it is a factor that can inform the implementation approach of the organisation. As R3 stated, the composition of the data is dependent on the type of organisation. This contribution is valid especially if one considers the modern organisations and their dynamics. A social media organisation deals with different kind of data compared to traditional organisations in the construction sector for example. The volume, velocity and variety of data is different from industry to industry as well according to R3. Technology giants like Google and Amazon rely on their information processing capabilities as they deal with high volumes of data in near real time. This is certainly different for organisations in industries like agriculture or mining. While any organisation in any industry can implement and benefit from data driven decision making, the approach and targets will differ from industry to industry or sector to sector. Failure to recognise an approach best suited for your organisations industry can compromise the benefits of the adoption or in the worst-case lead to failure.

5.3.8 Perceived Value

The perceived value of data driven decision making (DDDM) was not identified as a factor in the literature review but was identified in interviews especially through R4 and R6 who cited targeted value to be a factor. Considering that organisations usually look at the business case before adopting or implementing any technology, this factor is important. It does not only influence the decision to adopt but might also determine how much resources are channelled towards the adoption and implementation. The value identified include improved efficiency, market growth or improved customer satisfaction. If DDDM is perceived to be valuable by both management and employees, the adoption and implementation will receive organisation wide support and will increase the chances of success. However, if the perceived value is low or when there is doubt on the value, the adoption might not be approved. If approved, management might not channel enough resources towards the implementation which can lead to failure. Therefore, the value perceived to be delivered by the adoption of DDDM is certainly a factor in the adoption process.

5.4 Limitations of This Study

In our study we relied on seven semi-structured interviews to collect empirical data and our sample included both data analytics consultants and decision makers. We believe a larger sample size could have improved the validity of our research by getting views from more interviewees especially decision makers as we only managed to secure two. Also, applying research triangulation like using surveys together with interviews could have further improved the validity of our findings as highlighted by Patton (1999). Finally, our data gathering was limited to organisations in Sweden therefore the transferability of our research findings to other contexts outside Sweden is limited. However, despite the above-mentioned limitations our research laid a good foundation for future studies on the subject.

6 Conclusion

The aim of this research was to identify and describe organizational factors that are influential in the implementation of data driven decision making (DDDM) by answering the research question: "*What organisational factors are influential in the implementation of data driven decision making (DDDM)?*". Using literature review and empirical research through interviews, we identified management support, organisational structure and processes, availability of skills, organization size, organizational culture, change management, organisation industry or sector, and perceived value as factors that have an impact in the implementation of data driven decision making.

The results of this study confirm the significance of organisational factors as positive or negative influencers in the implementation of data driven decision making. Considering the emphasis of previous studies on technological factors, the results offer another dimension that can help organisations improve the success rate of adoption and implementation. From the interviews, it was clear that each of these factors can bring either positive or negative influence depending on circumstances. For example, when looking at management support as an influential factor, the interviewees highlighted that availability of management support is a significant boost to the implementation of data driven decision making. On the other hand, absence of management support will have negative influence on the implementation project.

In addition, the study provided detailed description of each of the identified factors and circumstances in which they can be enhancers or inhibitors in the implementation of data driven decisions. When considering organisational factors such as organisation size, organisation culture or organisation sector, it is important to be aware of how an organisation can take advantage of its circumstances to influence the outcome of its data driven decision making implementation. For example, the empirical results indicated that both small and large organisations can make use of their size to be successful. Agility of small organisations was highlighted as a positive influencer while larger organisations have vast resources and capacity to support the implementation. The industry or sector of the organisation brings unique circumstances which need unique approaches. Organisations in Information Technology driven industries like Amazon, Google and Facebook rely on high volumes and real-time data to support their decisions. On the other hand, organisations in sectors like agriculture might not need real-time data to support their decisions. Therefore, it is important for organisations to consider the identified factors alongside their unique circumstances.

Other factors identified such as availability of skills and perceived value of adoption are less complex when determining circumstances in which they are either positive or negative influencers. The interviewees confirmed that having skilled technical implementers and skilled decision makers enhances the success rate of data driven decision making adoption and implementation. More so, there is high likelihood of the organisation deciding to adopt data driven decision making when the perceived value is high. When organisations see data driven decision making as a valuable step, they are willing to invest resources to make the adoption a success. On the contrary, lack of skills and low perceived value are both negative influencers which can reduce the chances of implementation success.

Based on the results, it is also clear that the success of adoption and implementation of data driven decision making is dependent on the organisational structure and processes. When adopting DDDM, organisations need to ensure that both their structure and processes are aligned to the new way of making decisions. Larger organisations are more likely to require some form of restructuring and alignment of processes while smaller organisations might not need to make significant changes. How the organisation handles change was also identified as an important factor considering the amount of change that data driven decision making introduces. The ability or inability of an organisation to manage this change will determine whether data driven decision making will be a success or not.

In conclusion, organisational factors such as management support, organizational structure and process, availability of skills, organization size, organizational culture, change management, organization industry or sector, and perceived value of DDDM were deemed to be influential. Organisations need to consider these factors alongside their unique circumstances to understand how they can be positive in their implementation. Also, these factors are not entirely independent of each other, therefore it is vital to have a holistic view when considering these factors.

Overall, our study and its results contribute to the Information Systems research literature on data driven decision making adoption and implementation. The focus on organisational factors was important given the identified research gap. This research can stimulate more research of the same nature and close the research gap.

6.1 Further Research

This research identifies organisational factors that can affect the implementation of data driven decision making and further investigates to detail how each factor determines whether an implementation will be a success or failure. The results of this study can be complimented by further research focusing on identifying the implementation stages under which each of the factors is most influential. Also, further research can also seek to measure the impact of each factor and prioritise them according to impact.

Appendix A – Interview Guide

The questions in the guide were not asked in the order they appear in the table. They were just used to ensure the interviewer covers all the relevant themes.

Theme	Concept	Questions
Introductions	Introduction and Background	Introductions by researchers.
		Remind the participant of their rights, confidentiality and ask for permission to record.
		Can you please introduce yourself, your role and responsibilities in your organisation as well what your organisation does?
		The purpose of our research is to identify organisational factors that are influential in the implementation of data driven decision making (DDDM) in organizations. We look at DDDM as the use of data in the decision making and management process. Our research looks at a combination of Big Data and organisational decision making. Also, noting that the focus of many researchers before us focused on technological factors, we intend to focus on non-technological factors that influence the implementation.
Organisational Factors	General Question	In your opinion, based on your experience, what do you think are the organisational factors that influence the implementation of data driven decision making? • *This was only used as an opening question where the interviewee demonstrated comprehensive understanding of the topic in the introduction*.
Organisational Decision Making	Strategic and Operational Decisions	What type of decisions have you mainly targeted to support using data? Strategic or Operational or Both?
Big Data	Big Data Analytics	To what extent does your organization use BDA in decision making? How does that help optimize decision making in your organization?
Organisational Factors	Structure & Processes	While implementing DDO, has your org/clients changed their structure to embrace the systems? To what extent do you think this was a factor in the success/failure of the implementation? Who is accountable for decisions made using data? The systems owners or decision makers?

		How has accountability issues affected the use of data in decision making? Do you have a separate data office or department?
	Organisational culture	Do you consider your organisation to have a data-driven culture? Why? How has this culture situation affected the implementation/acceptance of data as a decision driver?
	Management support	What role does the management play in the implementation of BDA/DDO? Do you consider them supportive or resistive? Do you think this has had an impact on the success/failure of DDO transformation?
	Availability of resources and skills	What skills do you consider mandatory in this implementation? How prepared was your organisation skill-wise? What impact do you think this have in your implementation?
	Type of Decisions	How much success have you in supporting strategic decisions using data? How much success have you in operational strategic decisions using data? Do you think the type of decision affects the outcome of the implementation?
	Change Management	How much of your success or failure do you attribute to good or poor Change Management strategy? By Change Management we are referring to how you manage change to DDO.
Any Other	Any Other	Do you think there are any other influential factors that organisations need to consider when implementing DDO?
Conclusion	End	Thank you note.

Appendix B – Interview 1

Researchers: OM = Obey Mabaso (Lead Interviewer)
CZS = Conerlious Zecharia Sagandira (Transcriber)
Interviewee: R1
Work title: BI Consultant (former Revenue Assurance Manager)
Date and time: 23 April 2021, 10:00
Transcribed by: Conerlious Zecharia Sagandira
Checked by: Obey Mabaso
Date of transcription: 24 April 2021

SEC	PERSON	TEXT	CODE
1	OM	So, the way we split roles in this interview, I will be conducting the interview and Conerlious will be transcribing. The first thing that we really need to highlight is that we are not going to share personal details or company details of the people we interview. We will anonymize the analysis. Also, after our transcription, we will share the transcripts for you to confirm that we interpreted what you say correctly. We can start with you introducing yourself, the kind of role you hold and the industry that your company focus on.	
2	R1	I'm working at Company Y as a Power BI developer primarily. So, I'm working directly with the with the customer. I have a lot of contact with the customers talking to them about their needs, what they need to be able to understand the data that we provide them. Mainly in terms of different visualisations, ET cetera, in Power BI. I've been working with them since August 2020. So, I'm actually new in both the IT business and the consultant business. I've been working with revenue management before at Company Z. I worked with them for some years where the two last years was primarily with Power BI development. A couple of years ago they started to build a new Datawarehouse. I was then responsible to take usage of that data and create reports and tools for me and my colleagues to be able to do revenue management work. Before I worked with a hotel company for 15 years. Out of this, the seven last years was with revenue management. Before that I was actually working in the operations as the front office Manager, customer relations manager etcetera out on different hotels. I did not	BDA

		start within the data IT business. I started as an operations person and then I worked my way towards this position.	
3	OM	Congratulations on your new job and career path. Your profile is quite interesting to us. You have had a lot of experience as a decision maker and now a lot of the insights as the implementer of these technologies. So let me take this opportunity to recap the background of our research. We intend to identify influential factors in the implementation of data driven decision making. What we mean is, we need to understand what it takes for organisations to transition from point A to point B, where point B is where they rely on their data to make decisions. A lot of emphasis has been given on the technological side of things like which system do you need to implement? What kind of data do you need to gather for you to be data driven? But there's a gap on the organisational side, on the non-technological aspects of this journey, so that’s exactly where we want to understand, the organisational factors.	
4	OM	In your opinion based on your experience, what do you think are the factors that can hinder or enhance an organisation’s transition to become data driven?	
5	R1	I would actually say that the most important part is the employees, because you can get fancy data warehouses and tools etcetera as much as possible, but if you don't get the employees to understand how to work with the data, you can end up with having a lot of reports and systems, but no people using it and the challenge is to get the people to always rely on the data that you really trust. I've seen so many times people looking at data when they are going to take a decision, but they end up rather going on the gut feeling because I now know how it should always have been, how it's, how it should be in the future, ET cetera. I know this better than the system and the data. But it's always most often the best decisions are taken when you really trust the data and working with it in the correct way. So yeah, it's so much about getting all your people on board, on the journey to become data driven. Because if you don't get them with you, it's useless. You can have how much data you ever can get but it will just be useless.	AS, OC

6	OM	On the employees, I view them in two categories, that is the management and the rest of the employees. How much of an impact do you think the management plays in the successful implementation of these data driven systems?	
7	R1	Well, good question. It's very important for the management to really be always a step ahead of the team so that they can support them. I've seen Departments where you have a manager that doesn't really like to be data driven. Then you can't get that Department with you. It's really up to the management to support the initiatives. It is also about what kind of company it is, what organisation is it, how much data driven do they need to be to make the decisions. You know the department revenue management where I worked with, that was so much relying on data so every employee really needed to be able to understand how to work with the data, but then you can have department that doesn't work with data at all. So, becoming data driven is so much about what kind of organisation as well.	MS, OSP
8	OM	That's understandable. In your previous experience, when implementing these BI systems or transitioning from non-data driven to data driven, have you had to adjust the structure of the organisation or the processes within the organisation to accommodate the new way of decision making?	
9	R1	Wouldn't say that. I mean the organisation was quite slim from the beginning so I can understand in larger corporations that you may do reorganisations when changing the way of working. But I don't think that we really did it at all.	OS, OSP
10	OM	OK, so what I am getting from this is that the size of the organisation really affects how you will approach this implementation and probably affects the possibility of success or failure. Is that correct?	
11	R1	Yeah, exactly.	OS
12	OM	The other thing you mentioned about employees is knowing how to work with data. How big an impact does availability of skills in an organisation will have in the implementation of data driven initiatives.	
13	R1	Yeah, that's very much important. It's not always a need that everyone has the skills from the beginning, but what I've seen you need at least one or two within every	AS

		department that really have the skills to work with data and they then can teach their colleagues, ET cetera. But if you have a department where you have nobody that really has understanding of data, then it's very tough for the manager to get that department to become data driven.	
14	OM	When it comes to the type of decisions, between operational decisions and strategic decisions, which kind of decisions do you target to be data driven?	
15	R1	My department in revenue management was actually a little bit both because we were working both long term decisions, forecasting budgets, business strategies but also the day-to-day work that would have had an impact on today's or tomorrow's flights and their operations. And then of course data was of high importance in all those decisions.	SDM, ODM
16	OM	Do you feel like it was easier to use data in one type of decision more than the other?	
17	R1	It was 50/50 I would say. The day-to-day decisions we were taking was much about looking at data on what is happening in the close time window. The past couple of days. What travel patterns have we seen this week ET cetera? But in the long term, strategies were so much looking at long history, way back and then being able to forecast in the long term so.	ODM, SDM
18	OM	How did you handle change while implementing data-driven projects? For example, when you had to install the new Datawarehouse, how did you make sure the whole organisation was on the same page?	
19	R1	Well, I thought it was much up to every department because it was quite a big project implementing this Datawarehouse. For my Department, it was much that the strategy was mostly to have me looking at what kind of data we would be able to get and to translate that for my colleagues in reports and tools and then really have workshops with them talking about how to use this data and what is it for and what kind of decisions can we take out of this, ET cetera.	OC, OSP
20	OM	I can see you sort of delegated change management to department by department.	
21	R1	Yeah, I would say we did have something like that. But we had a group within the company where there were	CM, OSP

		representatives from each department in the company where we coordinated with each other but the implementation was at department level.	
22	OM	Did you consider yourself as very data driven?	
23	R1	We were able to become quite data driven. We were quite data driven compared to what we were a couple of years before that. Every Department worked with their own business systems that were producing data relevant to that department. Altogether, we were able to take decisions based on information from departments. So we became much data driven.	BDA, OSP
24	OM	Do you think Big Data is a requirement to become data driven?	
25	R1	Well, I would say any data is enough. I mean, you can become data driven with small amounts of data, I would say.	BDA
26	OM	Do you feel there are any other influential factors that we might not have touched on?	
27	R1	I've highlighted the importance of getting the employees with you to become data driven and that any data can make you become data driven if you use it correctly.	OC, AS
28	OM	Thank you for reserving your time for this interview. So we're going to transcribe the interview. We will share the transcript with you so that if you want to clarify something or maybe we might save misinterpreted something that you have said, you can help us correct that.	
29	R1	No problem, good luck with your work.	
30	OM	Thank you so much.	

Appendix C – Interview 2

Researchers: OM = Obey Mabaso (Lead Interviewer)
CZS = Conerlious Zecharia Sagandira (Transcriber)
Interviewee: R2
Work title: Chief Financial Officer (CFO)
Date and time: 29 April 2021, 13:00
Transcribed by: Conerlious Zecharia Sagandira
Checked by: Obey Mabaso
Date of transcription: 30 April 2021

SEC	PERSON	TEXT	CODE
1	OM	So, the way we split roles in this interview, I will be conducting the interview and Conerlious (CZS) will be transcribing. The first thing that we really need to highlight is that we are not going to share personal details or company details of the people we interview. We will anonymize the analysis. Also, after our transcription, we will share the transcripts for you to confirm that we interpreted what you say correctly. We can start with you introducing yourself, the kind of role you hold and the industry that your company focus on.	
2	R2	Yeah, of course. No problem. Well, I am R2. I work as a CFO of a business area within the Company X group in Sweden. We have operations in parts of Europe and we are actually entering the US with the group right now. I have been in the group for 14 years now and I have been working in the accounting and business side for a few years and the last five years I have been working as the CFO. I have been working with BI for all those 14 years and I am more or less the responsible person for the total system at Company X. I am not working with development with all the business areas, but I am the one having the	

		contact and working with the steering groups of BI in the group.	
3	OM	Quite interesting. Is it correct if I categorise you as a more of a decision maker than an implementer of BI systems?	
4	R2	Yes	
5	OM	So, we move onto the main part of our interview. On the background of our research. Our purpose is to identify the influential factors that influence the implementation of data driven decision decision-making. So here we are just looking at the use of data in the decision-making process. We also realise that other researchers that came before us focused on the technological factors like availability of technology and different systems. We are focusing on non-technological factors specifically organisational factors.	
6	OM	What type of decisions do you target in your company when using data to support decisions?	
7	R2	Yeah. Well, it differs a little bit between the business areas. If we take a look at the one of the business areas that is named the Unit X they are very, very driven by data concerning the customers following up the possibility, the volumes, and trends by each customer. So, there is very much market focus or customer focus on the data they work with. Of course, they are a kind of trading company, so of course the trading part of buying and selling in the big picture is important for them. In the business area where I am, we work with production, it is much more operative data we work with. We work with the yield and the waste in the production facility following those up. Looking at the yield of course we can see how our possibilities change overtime. To customers, we are looking at the product mix to understand our possibilities because product mix changes the possibilities for us because some segments are more profitable than others. So, when changes happen, we need to understand those changes. So, it is little bit more operative. I think that's the two cases that we work with.	ODM, IS
8	OM	Okay. Then do you have any strategic decisions that you support using data.	
9	R2	Well, I would like to say yes on that one. We are making very much important strategic decisions but it is quite	ODM, SDM

		operative information we get and of course we make decisions based on those but it is not on a very high level, I think it's much more used in the daily operations, the information we get. And of course, we see trends in the data that gives us input for strategic decisions, but it's only a part of the decisions that we make that comes from the data we use in our BI system.	
10	OM	On the data side, to what scale do you use data? Do you consider your organisation to have reached the Big Data level or it's just some form of data that you're using?	
11	R2	Well, that also differs, at Unit X, they're much more data driven company than we are in the production side. Unit X uses much more data from very many sources, and I think that's what you mean by big data. And they are working with the data warehouse. Getting all the data into one place and then use it in different user applications. They extract data from every store to have information about those and they fetch data from the sales and put all those together. So yeah, part of the Company X uses little bit more big data. The production companies are using much more of their own data from the ERP system to get the information need.	BDA, IS
12	OM	When you started implementing the data driven initiative, did you establish within the organisation a Central Data Office or Department that focuses on the data?	
13	R2	Yeah, well it is segmented into units, but within the units we have teams working with data.	OSP,
14	OM	Do you think this might have an impact on the success rates of implementation?	
15	R2	Yes, yes, I believe so that it will influence how we work with data.	OSP,
16	OM	Besides the technical side of the data, did you have to adjust any structure to suit the new way of working, being data driven?	
17	R2	A little bit, not very much, we say.	OSP
18	OM	OK, as you mature with the data driven cause. Maybe as you start using more and more data. Do you think how the organisations is structured will impact the success rates and how?	
19	R2	Well, yeah, I understand the question. You need to understand a little bit that we are not a very big	OS, OSP

		organisation like a global company with hundreds of white-collar employees. We have Unit X office in Gothenburg and they are about 30 people or 35 people. Then at the production company, we are quite a traditional production company which means that we are working with optimization to get the data out as smooth and as effective as possible, and we of course try to push the data out to the organisation where it's needed. But we don't have any very big organisation working with the data.	
20	OM	I understand. So, in making these data driven decisions in your company, who has the accountability. Did you have to shift the accountability from the decision maker to the system owners or the decision maker still has accountability.	
21	R2	Yeah, well that's an interesting question. I think that we are still at the level that the manager has to evaluate the data and have to put some own intelligence into this decision.	OSP
22	OM	So, it means they retain their accountability, which is understandable.	
23	R2	Yes.	OSP
24	OM	Do you think the Organisational Culture has an impact on the implementation? By Organisational Culture I am referring to the values shared by everyone in your organisation. E.g. Data driven culture.	
25	R2	Yeah, I would say so, very much that data is available and usable in the organisation, so I think that very many people appreciate the data and use it. We are getting questions and assignments from different kinds of users to keep on developing the data and the structure of the data to give them even more help in their work. So yes, I would say that this has an impact on the implementation drive.	OC
26	OM	When it comes to your management, which I believe you are part of, what role does your management play in the implementation of BI or the implementation of this data driven culture?	
27	R2	The management is very interested to keep on developing the availability and the value of the data that they are a part of this very much, yes. Then I think that we have not created data information system only for our	OC, MS

		managers, we are creating data for all employees needing that data. So, it's very broad use of the data.	
28	OM	I can tell that the management has been supportive when it comes to data driven culture, but in your opinion, do you think this has had positive impact on your implementation?	
29	R2	I would say that the management is very supportive and their support has been a part of the success of creating the data driven culture in the company.	MS
30	OM	That's great. What do you think is the impact of skills availability in your organisation when implementing such initiatives?	
31	R2	The success there is created by two sides. One is that the management is requesting more available data and more accurate data. Then going to station that works with the data and creates the models, they need to educate themselves to be better. Quite often we work with one or more consultant companies helping us with the back-end codes in the models. The better we are in our own organisation, the better the project develops, the better the success rate is, so the better we are, the better models we create. So, we need to understand the software we are working with. We need to understand what we actually need and what the management is asking for. So, I think that is a very important thing in this, because I guess that you know that if we go to consultant companies like, yeah, like the big ones that sell solutions for Qlik View or Power BI or something like that. They will show you very nice dashboards or something like that, but it is quite often a long way from showing that screen, very nice dashboard to actually going there because you need to understand the data that you have and the data that you need. How things work in the ERP system, what you might need from external data. So, the better we understand it, the better the success rate it is.	AS
32	OM	I will take you back to a question that I touched earlier when we started, about the type of decisions between operational and strategic. Do you believe a data driven culture is more suited to one type of decision or it can be applied to both?	
33	R2	I think that both are very important because on the daily operational basis, operational information is needed.	SDM, ODM

		But looking at the trends, the big picture trends, yes, that is equally important. It might not change from day to day, but looking at the things overtime, it's important for strategic decisions that that we make.	
34	OM	Okay, then on the technical side of your implementation. You mentioned that Unit X side is more data driven. Have you reached decision automation level?	
35	R2	We are headed towards ultimately optimization. We are partly there, but not totally finished with that one. So, we are aiming for more optimization at Unit X, which is the more data driven organisation in the group.	BDA
36	OM	Okay. How important is change management in the implementation and how have you handled it in organisation?	
37	R2	I think its combination of very many things. Some projects might have needed a roadshow going out to the different sites informing them about the new project. Some other initiatives might be a result of some workshops together in teams too. To gather information and to form the model that we aim to develop. So, I would say it's all over the scale, all from Roadshow getting out informing showing the initiative or having one or two people working with it and then introducing it by mail. It depends on the project. Bigger projects might need a roadshow, smaller changes might only need an email informing that now this is working and it's up.	CM,
38	OM	You mentioned that there is a lot of management support. How much of an impact do you think the rest of the company, other people not management staff were influential in the success of this data driven initiative?	
39	R2	Yeah, I think that it is good when we have a broad perspective more from the management, not only a few users but all management need to backup things. We would need to have all managers on board going forward, this one because everyone needs to understand the importance of the data and the importance that we get accurate data in right time. So, I would say that everyone needs to be with us in this one.	MS, OC
40	OM	The last question, do you think that there are any other factors that we might not have touched that were influential in your organisation during this implementation of data-driven or BI systems?	

41	R2	Yeah, I've been to two conferences with Qlik View in the USA a couple of years ago and I know that what we got the really big companies working with Business Intelligence systems like General Electric and other really big companies. And then we got the very broad scale down to very small companies using Business Intelligence just to take out data, then give them a little bit more structure. So, I think you're working with the upper side of the scale. With larger companies, just, is that correct?	OS, OSP
42	OM	We intend to capture the whole scale and if size is a factor, we also need to capture that.	
43	R2	I understand, and I think that in many situations if we take the lower 50% of the scale from biggest to smallest. I think that quite often there is one or two persons in those organisations driving their business intelligence work. And they were both with some kind of demands from management that we need this kind of information and on the other hand they can also work with information they know is available in the system to make something good out of it. I think that's the two ways to work with the data in those type of companies. Many companies start with a very low level. Just getting a small-scale model out or something like that and then they get a little bit curious and say okay, how can we handle this type of information? How can we do that? And it grows. Quite often we work with some kind of ad hocked project. We know that we want something, but we really, really don't know the road to that place. Now we sit down in some workshops with maybe some consultants that that could help us. And we try and we have some kind of try failure, try again and then we will try to get there. I would say that more than 50% of our projects have been in that Ball Park. Looking at things that we think we can use this data and we try and quite often we succeed when we work as a team because we have different places in the organisation, we have different kind of knowledge about systems and what we need so, so that's quite often works well and I think that's the way many companies work with Business Intelligence. Then of course we have the really big companies with whole Department of Data. People working with the	OS, OSP, AS,

		data and creating the models they have in house knowledge and that kind of stuff. And I think we are somewhere in the middle on that scale. We both work with ad hoc solutions and then sometimes we have bigger projects like we did put together a finance application looking at finance from 20 different ERP systems. And that was a big project which involves a few people and we have a project leader. But sometimes we work with small projects with no project leader.	
44	OM	Thanks a lot. That was quite informative. Let me just take this opportunity to say the thank you for reserving part of your time to talk to us.	
45	R2	Yeah, and if you have any more questions just send me an email.	
46	OM	That's fine, thanks a lot.	
47	R2	No problem then. Good luck with your project.	
48	OM	Yeah, thank you, thank you.	

Appendix D – Interview 3

Researchers:	OM = Obey Mabaso (Lead Interviewer) CZS = Conerlious Zecharia Sagandira (Transcriber)
Interviewee:	R3
Work title:	Principal Consultant Data Analytics
Date and time:	29 April 2021, 14:00
Transcribed by:	Conerlious Zecharia Sagandira
Checked by:	Obey Mabaso
Date of transcription:	30 April 2021

SEC	PERSON	TEXT	CODE
1	OM	The first thing that we really need to highlight is that we are not going to share personal details or company details of the people we interview. We will anonymize the analysis. Also, after our transcription, we will share the transcripts for you to confirm that we interpreted what you say correctly. So probably we will start with the introductions, mainly what role do you have at your company?	
2	R3	Yeah, I can introduce my role here at Company X as far as I know it, it's always a moving target. I'm being employed here as a consultant, as a senior principal consultant working with analytics in the big team in different angles because it has several areas that all relate to data but different kinds of data. There's a strong presence of ERP systems here, ERP development and implementation within our clients. That ERP is usually a data source when you work with analytics. It focuses on how you define the workflows, how people should work, the processes of purchasing and sales and many other matters of interest that comes in as a supporting tool to reach the goals that you have when you implement a system.	BDA
3	OM	Quite interesting, so to move to the next segment of the of the interview. I will be conducting the interview with Conerlious (CZS) and he will be helping with transcription. So just to recap, our main purpose of this research is that we intend to identify the	

		factors that influences the success rate in the implementation of data driven systems, these are business intelligence tools. What we mean is basically what does it take for an organization to transition from that place where they were not using their data that much to a place where they are usually relying on data for decision making.	
4	R3	Yeah, that gives good meaning because many clients I met and also those I have been meeting, they took a short period like here at Company X, but previously in other companies, they are not necessarily that mature when you initially contact them. They have an idea of what they want to get, but they do not understand the force or the possibilities they have when they have data. So, it's usually about getting them to start the journey. If they don't start, then they don't understand it at the beginning and they may ask for a report or they ask for an implementation of an ERP system, and the report comes in as a handy second thing, something that they think is probably important, but they don't know the importance of it until they start working with it. That is when they start seeing why need to change, what they need to do in order to be data driven.	OC, AS
5	OM	So, in your opinion, from your experience, what does it take for your organization to successfully transform from point A to point B? Point B being they are a data driven organization. What do you think are the factors that affect this transformation?	
6	R3	I think it's critical for leaders at all levels to make sure that they train their employees to always bring data which supports decisions, that will also help by making sure every employee appreciates the use of data to make decisions. These decisions can be operational which will be used in the future to make strategic decisions. Leaders need to emphasize how important it is for employees to always bring data which supports the decisions that the manager has to make. So, leaders have to practice this way of asking employees to prove data that supports decisions. This should start from the CEO and it goes down into the hierarchy of the organization and comes all the way down to the operational level. If the	OC, MS, OSP

		managers rely much on gut feelings yet they know there is data which can be used to make decisions but not using it, chances are high that the organisation will not be successful in their implementation. Then there's another one. The aspect that I think is very relevant to this company is that when you implement ERP, you always figure out the processes. How do you work when you make a purchase? What are the steps that you do when you buy something or sell something? By defining those steps, those workflows, you also define the decision points in that. You'll also be able to tell them what they need to have in order to make a decision.	
7	OM	Okay. On the structure of the organisation. Do you think that the structure and processes of the organization may affect the success of the implementation?	
8	R3	Yes, I am not sure that is necessarily always the biggest obstacle whether you have a flat organization or many hierarchies. I would say the biggest obstacle is that you have managers who just want to do it the way they're used to doing it. They construct the statistics which they can use as the evidence that supports their decisions. Managers should have an understanding of the objective goal to be able to use data for decision making rather than relying on their instinct. This could result in the implementation failure because due to the structure of an organisation that only managers are decision makers, they will still keep on making decisions based on their gut feelings which affects the whole implementation part. So, the top leaders need to always make sure that their managers provide data which supports their decisions.	OSP, MS, OC
9	OM	Very informative.	
10	R3	Yeah, it’s an interesting subject.	
11	OM	It's actually quite interesting. How much do you think trust in data affects the implementation of data driven decisions?	
12	R3	Yes, and that's a real danger too, A good example: If you're very control-oriented, you can get very upset when you look at two reports and there's a	OSP, OC

		difference of a few dollars or so when the totals are in millions and you cannot trust the data anymore because you are getting results which are not accurate. On the other hand, if you're looking at a trend over months or years, it doesn't really matter if the exact number is different. What is important in that case is that it shows a decline or a rise. Maturity of company also matters because the more they get matured in using data is the more they trust their data which they give to the audience. One thing to achieve this is that all decision makers should take that into their own hands and not just let a department of IT or a third party do those insights because that's going to help them trust their data more. In the long run we see that happening because the tools that work with those insights are getting easier to use, but it still takes some knowledge and skill to make decisions that can be trusted. If you're a very stable thinking person who loves to see numbers, hard core numbers in columns and rows to be able to trust the data. You might have a hard time understanding or trusting the data because you will be expecting to see table, graphs and columns but what matters sometimes is just the visual part. So, there's a lot of aspects to consider when you're trying to be data-driven at all levels. I would say that you need to be more visual at the operational level and also at the top level because CEOs don't care about numbers. They want something solved and visual presentation showing if it is good or bad?	
13	OM	So closely related to the issue of trust when you are now relying on data in making decisions. Who is accountable for the data-driven decisions?	
14	R3	Rule number one: if you have a decision support system of any kind, it is always the fault of the system if something goes wrong. It's always the system's fault first, so the system owner must have an efficient way to show whose fault it is. If the numbers don't add up, is it because an employee entered something wrong into the system, or are there other inconsistencies? It could be the decision support platform where something is very wrong. But in very many cases, it's a human factor in the value	OSP

		chain because the big system is always the last system to indicate something. All the errors add up to that last point. A decision maker would never realize that it is his mistake. It's always someone else's mistake, and if you keep that in mind when implementing a decision system, you can deal with it. You just need ways to support it. You need good first-line support, usually a network of ambassadors throughout the organization who know the data and how it works and how it relates to each other. This can explain. From the perspective of IT, you need to make sure you have good traceability so you can track things. You can trace the data back to its source, and then you can probably figure out who needs to correct what. But if you have several of these issues with data showing up incorrectly, then the whole system and trustworthy. Because even if it's not the system's fault, let's say that all the sources it's using are generating bad data, and that bad data is being displayed in the same system, then the system is not trustworthy. In that case, you need to rename it. You need to work properly, find the root cause, and reintroduce it under the new name. That's what I would say,	
15	OM	Yes, I understand, and what I'm reading out is that it's a collective effort by management and everyone. What impact does the Organisational Culture have in the implementation of data driven decisions?	
16	R3	The important thing is that the management must be aligned and have the same level of understanding of data with all employees. When entering data, managers should inform employees so that they know why they should do it correctly and what is expected. One of the most important things is that managers are usually not the ones who are creating value in a company that they manage, they only manage those who create value. If you have a decision system, you have it because you want to improve something. Then you want to make people understand what is expected and do things differently. This means for them to do differently; they need to	OC

		appreciate how data is being used in a company to make decisions and the value it is bringing.	
17	OM	What type of decisions do you normally target within your systems? Do you target more strategic or more operational decisions?	
18	R3	Usually, when we approach companies, they are more occupied with their strategic decisions because that feels more important. But those decisions are usually already served in some way by the company. On the other hand, it is also important to consider operational decisions which are used to serve something on daily or hourly basis. So, these decisions can be later be turned into strategic decisions in the future. This is done by aligning strategic and operational decisions so that they connect in a way that strategic decisions will be supported by operational decisions. So, we are usually doing both, but they do not always come in at the same point in time.	SDM, ODM
19	OM	In terms of the success rate, do you feel the type of decisions will have an impact? Strategic vs Operational decisions?	
20	R3	If it's a classic closely related to ERP systems, I'd say the operational would be the most successful because they have defined operational steps and I to support them. On the other hand, if you do strategic implementations, then it's a smaller target group, you can better interview them and find out what they need in the format they can handle, and they usually have something from before which you can inspire you or you can make the transition to the new system easier because it won't be completely new for them. I would say that working with strategic decisions is easier. It is easier to both become successful and easier to not to get into difficulties.	ODM, SDM
21	OM	In your role as a consultant, I understand you have helped a lot of organizations when it comes to the skills within the organizations. I would guess that if we are not just focusing on the skills of the technical people implementing systems, we are also looking at the skills of the decision makers. I think that's an important signal.	

22	R3	So that is very important, because if you want to become data driven, truly data driven, you must have the skills of working with the data and the tools as well. If you don't have that, if you only rely on somebody else doing these things for you, then they become a bottleneck and. Someone won't get served information at the speed you want. You can have a parallel with a lab to compare it to secretaries. Back in the 70s and 80s, you had a whole haul of secretaries writing letters and contracts and whatever it was they were writing for the different bosses and the people around them. This means you have very few ones today as they do something completely different. Everyone is responsible for creating their own letters, writing their own letters. That's natural, nobody asks to have a secretary to do these things anymore, and we should have the same. We need the same movement within data analytics in in a few years' time.	AS, OSP
23	OM	Yeah, of course, we've seen a lot. I mean, the self-service agenda appears a lot in literature, and it seems to be a huge thing then they in the interest of our time. You mentioned that there's a need for change within the organization like IT management level at all levels to appreciate the need for these data driven organization. Now, if you don't like that change management in organizations, maybe within your organization, in the org and the organizations that you have assisted in implementing these systems,	
24	R3	That is one effect of being a client facing BI consultant means that you've become like a spider, you have a lot of arms around, you do a lot of things. You do a lot of technology and you do a little bit of understanding of the culture of a company. Change management is one of those parts that you do and you, but you don't do it like a change management consultant because you're not skilled enough for that. But we come across these different needs, so we become like a Swiss knife. If it's a good	OC, CM

		initiative, you would think you would connect these really good people into these processes. You have a change management consultant when you implement the new system because you don't just implement a new system. You always implement new ways of working, new ways of taking decisions, a change in your organization, whether you want it or not. That is always the result. Take it seriously. You also collect and make sure that you have the right competencies available when you do that, because that is the effect. So, that is very important.	
25	OM	Oh, I see, then probably the second last question and how do you measure the success in this area, determined to say this is now a truly data driven organization, and do you think your clients understand this measure?	
26	R3	That's an interesting point, because I think data driven as a phenomenon is not reachable. It's lack of vision. It's like there is a sign you want to go there, but you will never reach the completion of it all because one of the parts of being data driven is actually to take away human decisions. If you automate things, you replace humans after that automation. Either mechanical decisions or algorithms, there are always boundaries on how you evolve. So, when you have reached a certain state, there is so much more to do. We haven't seen the stop of it. What is the ultimate data-driven organization? When I worked for a municipality, we joked about it being an on and off switch; you turn one of the stabilizers on, make decisions, make sure people get educated, take care of the children with robots or whatever, and then they turn it off, Is that the ultimate data-driven organization? Uh, I don't know. But when it comes to a successful initiative in striving there, it depends very much on how you have defined the project. When you begin the journey, what is the goal of a certain initiative? Is it like one example I had working with the care of senior citizens? Was that all the meetings were discussing the past? They were discussing what they	OSP

		did and what they didn't do in the past and if it was good or not, they never talked about the future. So, we implemented a system with a plan, things ahead, a plan, what they needed to do, and it kind of became an ecosystem of information and they started to discuss the future. So, we see a great need coming in three weeks. What should we do? Should we hire people? Should we reschedule them or what should we do to meet this increased demand? If you are good at implementing these things, you would have caught this need for change before and then you can evaluate what has happened. Have people changed the way they do work? But you must have some kind of definition of initiative. Why do you do it? Because if you like, I have also been doing the initiative part, just because you want to do it because you think it's cool and all the other organisations are doing it. Then nothing changes and it's a failure. So, um, it's a very good question. When will we be data-driven? This is when a company is data driven and to a certain extent, I would say that all businesses with more than a few employees are data-driven, but this is not the case. You know, I've reached that level because when you do that, there's so much more to do.	
27	OM	That pre-empted my next question, I really wanted to understand if it's always a must to have big data for you to become data driven. Is it always necessary to have big data?	
28	R3	No, I don't think all companies need that. Some companies have a very easily predicted value chain. They don't need that, but I think it is also about the size of companies and their industry. In some industries they need to use huge amounts of data to get value and some organisations can still be considered data driven by using small amount of data since they just use it to make simple decisions. It also depends with what one wants to achieve by being data driven. For a company that needs to make investments based on what the	OSP, OS, IS

		data is showing, they might need to have a surplus of data and the skills as well.	
29	OM	Quiet, interesting! So, do you think there's anything else that you need to comment on this topic altogether?	
30	R3	Oh, I would say that it would be interesting because I've been thinking of the data driven culture thing, I think it will be nice having decision makers being fully automated robots because humans always put other things into it such as their instincts. But on the other hand, it's really interesting because we always know more than the facts form the data. So those who are creating the fundamental insights are sometimes limiting the insights from the data because they know what should have been done according to your instincts. Things like if they know there's a pandemic going on or they know that the weather forecast is like this or you've been doing things before in your previous life that have made you gain experience in a certain way, all these things are important to also take into account.	OC, AS
31	OM	Yeah, thanks a lot for that. I don’t know Conerlious, do you have anything, or we can conclude?	
32	CZS	I think we have captured everything we wanted actually.	
33	R3	Thanks a lot for that.	
34	OM	If you have any questions, when you listen to the material or digest it, just feel free to contact me again for explanation's or so.	
35	OM	Okey. So, going forward, there's something that we just need to emphasize. In our analysis we will anonymise your details, I mean we won't share personal details and your company details as well. We will replace your name with some sort code names. No personal or company details will be shown in the transcript, after transcription, will share the transcript with you so that if you feel like you need to add something or there's an area where we might have misinterpreted and you can assist us before we do the final analysis and also the final reports we intend to share, if you you're interested in seeing the outcome in the legs.	

36	R3	Ok, that would be great.	
37	OM	Thank you. Thank you.	
38	R3	I think it would be nice, uh, following your career now	
39	OM	For sure. I'll keep in touch, OK!	
40	R3	Thank you. All right. Bye. Bye.	

Appendix E – Interview 4

Researchers: OM = Obey Mabaso (Lead Interviewer)
CZS = Conerlious Zecharia Sagandira (Transcriber)
Interviewee: R4
Work title: Project Manager – Data Analytics
Date and time: 30 April 2021, 10:00
Transcribed by: Conerlious Zecharia Sagandira
Checked by: Obey Mabaso
Date of transcription: 1 May 2021

SEC	PERSON	TEXT	CODE
1	OM	The first thing that we really need to highlight is that we are not going to share personal details or company details of the people we interview. We will anonymize the analysis. Also, after our transcription, we will share the transcripts for you to confirm that we interpreted what you say correctly. Can you start by introducing yourself and explain your role at your company?	
2	R4	So I'm working as a project manager and one of the things that I'm working with is about data. So I'm working within R & D because we're within a company where data is super important because we want to make data driven decisions. But we don't have the data that we need. The question is how then can we create that data?. What tools and processes do we need for it? So that's what I'm working with.	
3	OM	Okay, that's fine. Thanks a lot for that introduction. So maybe before we proceed, I will recap the purpose of our research. So what we intend to to capture the influential factors in the implementation of data driven decision-making. What we're just trying to do is to see what it takes for organisations to make use of their data to influence decisions. We have noticed, especially in literature, that a lot of organisations have already made decisions that they want to become data driven. Also, there's been a lot of focus on the technological aspect of data driven. They look at what systems they need, what kind of data they need, but there is a gap from people's side when	

		it comes to this journey at organisational level. That's where we want to focus on. So with our research we are saying, other than the technological factors, what organisational factors that organisations need to focus on? That introduces my opening question. In your opinion, and experience as well, what do you think are these factors that organisations need to be aware of other than the technological ones?	
4	R4	So first, you need to know what data you are working with. This includes knowing what your data is, and this is different for different companies and the type of company matters too. Some other things may be size of the company, how big it is, how much decisions need to be made. You need to really understand what your company wants to achieve by using data, what type of data are we working with and which data do we need? This means that you need to create data models for that, when you have all that, you now have a clear picture of what type of data, which data points and what tools and processes are needed to get that. This should be done, otherwise you won't have a successful implementation.	OS, IS, PV
5	OM	So you mentioned about the type of company, do you mean company size matters as well?	
6	R4	Nothing about size. It's about what you're working with, if you're working with building a house. You need those type of things, if you're working with IT, building computers or whatever other types of data. Size does not affect anything in my opinion.	OS
7	OM	OK, so this means in an organization, do you think that the structure or organization's structure will really impact the path to become data drive?	
8	R4	No, no.	
9	OM	OK. You also mentioned about the processes. If you're working with data and the likes. If you had to change the processes so that they are tailored to suit your needs and if its working, do you need to change the data strategy as well to suit whatever process which is being used or it's the other way around?	

10	R4	So there are different types of processes we can use, but we should only have processes that are important for the work we're doing. Then in those processes, we need to create data that suites those processes. So, either side you need to change the processes, then you get the data you want.	OSP
11	OM	OK. Then when we looked at the literature, we ticked a few things that we need to confirm with you as an expert in the field to put on the building of these systems as a decision maker as well. One of the things that kept on being repeated in research is largely done before us in the management supports. Does this mean the management needs to be part of data driven transformation for an organization to be data driven?	
12	R4	Yes, of course, it must be management supported. Both having a decision that is data driven and then making sure that people have time working with it.	MS
13	OM	Then there is an issue that kept coming up is the trust, giving people trust to the data, does this have any impact on the data driven transformation of a company?	
14	R4	It is a big issue because no matter how hard you ever work on your data; you would never be correct. It would always be the errors in your data, because at some point it's a human doing something. So the data will never be fully correct and trusted. To trust what you see, you need to understand that. You need to understand the basic data and you need to understand the calculations and the new information you get, that’s how it works. For each and every person to trust the data, they have to understand it.	AS
15	OM	Oh, yeah, that's quite an interesting observation to say that human beings will never be 100% correct to make data trustable. So, what are the measures that you normally take to make sure that people were making these decisions and trust the data even more? Because I understand you might have the technical knowledge of where the data is coming from and how you have processed it. But from the end user, we might not have much visibility on the journey of how the data travelled from raw data to	

		the insights. How do you make sure that they can trust that data?	
16	R4	You need to explain it for them to be on the same level. So where this data comes from and how it has been calculated, so you need to explain it.	OC
17	OM	OK, I understand that. So in your department, have you had a situation where you felt like you were less data driven than you are right now, I just want to understand the journey that you travelled in that transformation, especially in changing the culture of the people, because if you give way to people who are used to using their gut feeling, intuition to make decisions now, telling them to look at the data first and sometimes maybe the data is contradicting their intuition, how do you deal with that situation?	
18	R4	So first, I always think you should trust your gut feeling. Data can never replace your gut feeling, but data should be an input. So if my gut feeling says yes and the data shows me the opposite, then I need to ask why? Why do I have this gut feeling and why does is the data showing something different? So maybe my gut feeling was based on something that I haven't understood or have partial picture of. Then I need to learn more and understand why the data is wrong. So data cannot replace a gut feeling, it should be something that you use when you make decisions together with your gut feeling on it.	OC
19	OM	Interesting. So do you think data should support our intuition or?	
20	R4	Yes! we are not computers and we shouldn't be.	
21	OM	Then there is another thing that keeps popping up which is the availability of skills in the organization. We are not just looking at the skills of the people implementing policies, but we are looking at the skills of the people who are making these decisions as well. If you think that is the case, can you explain why?	
22	R4	I think you need to have some basic training so you can read diagrams and charts and understand some basic concepts. You need that. Then depending on	AS, OSP

		where you are in the organization, you need to understand your data, your what you see daily. Maybe you don't need to understand everything else but that of stuff. Some training is needed.	
23	OM	The other thing that is linked to the tasks we always made this question to say, if we become data driven and I am a decision maker, who is accountable in the decision that we make, I think it is partly answered this one when you say this, if you will, take the decision, maybe it's 50/50 between the system and the human. Do you think the responsibility might be shared between the decision maker and the system owner?	
24	R4	It's always the human, the decision maker. That's how we work. The top manager has the ultimate responsibility for every decision made in the company. Then that top manager they are responsible of firing people that are not doing a good job, but it's always the top person that has the ultimate responsibility for everything.	OSP
25	OM	OK, yeah. It's quite interesting because let's say I'm a decision maker and I know it is me who is accountable for every decision in the system. Won't these decision makers be tempted to ignore the data?	
26	R4	To ignore the data, what do you mean?	
27	OM	Yeah, to ignore the data, then trust their intuition hundred percent without looking at the data.	
28	R4	Well, they need to base it on something, and if you're a data driven company, you should look at the data. So, I told you earlier, if the data is contradictory to what you think, you need to dive into why and understand why.	OC, BDA
29	OM	Then the other issue is going to change management, especially for organizations that are coming from maybe let's say maturity in this data driven chain, trying to make some progress towards maybe a hundred percent or something like that. How can they make sure that they bring on board everyone not leaving anyone in the old way of doing things?	
30	R4	I think training, understanding what data could give you and then training again. Also, I think if you've been in a small context where you see all the data	CM

		already, all the tables, then you can use it. But if you see the big, big data with big data, like millions of rows, you cannot see that. You cannot have it on your desk and see it in front of you. Then you need to start trusting data and calculations and to show that we cannot have these two tables. That's not enough. We need all this and you cannot have that. You need to start trusting the systems.	
31	OM	OK, trust is something that is keeping coming back on this one. I hope, Conerlious (CZS), you are taking note of that emphasis on the trust that is needed to build on the type of decisions. We understand in an organization that decision makers might make different types of decisions. But we have two main categories, like the operational decisions, which are the day to day running of the business in the strategic decisions which we consider to be long term. I think the these are the type of decisions that you intend to make is in implication on the success of this transformation.	
32	R4	So when you're looking at long strategic decisions, you can only look at history and how has that been before and then what is typical? Then I guess you need to trust your gut feeling a little bit more when you look at long stretches of the future, looking at the data you have then gut feeling of that day-to-day operational data is more hands on.	SDM
33	OM	OK, but just to understand, do you think you can say many organizations have had more success in becoming data driven when it comes to operational decisions than they've become in strategic decisions or it's still 50/50?	
34	R4	I don't think I understood the question of what you want to know, really.	
35	OM	So I can explain to say that we have noticed, but probably some people feel data driven culture is more suited for operational decisions than it is for strategic decisions. So basically, that's my question to say, do you agree with this or you feel like it's going to be applied for both sides?	

36	R4	OK, I think it can be applied for both. But as I said earlier, you only have data about the history. But you have to consider what your gut feeling is saying. That is a combination of your own experience and knowledge and things you have learned. So to make those long term strategic decisions that are data driven, what has happened, what is happening around us, what type of decision do others around me make, what are they believing about the future, Is everyone going left, should we go right, maybe if I have other data information that tells us we should go right. But if everyone else is going left, maybe I should think of why are they going left, why do I want to go right? So I think you can have data driven in both operational and strategic decisions.	ODM, SDM
37	OM	Now I understand. But then earlier you mentioned that the size of the organization doesn't really matter in their success. So you feel like the general steps that the smallest or the SMEs will have to travel in implementing these data driven decisions still remains the same as those big organizations and buildings?	
38	R4	Yes, it's the same steps you need to go through. If it's a big organization, then more people need to go through it, then if it's a small organization, it's the same steps.	OS, OSP
39	OM	So it's a matter of just scaling up the operations in terms of the number of people and probably the effort that is required. So one thing that we have noticed is that some companies actually implement a separate data office using different names, probably that big data warehouse with the chief data officer. I'll begin to think this is just because I don't want data or it's actually something that is important for an organization to implement a dedicated office focusing on data.	
40	R4	So It is problematic because each organization within its big organization, you have smaller departments that whatever you want to call it, and it's that department that knows their data and you need to have that knowledge. It's not enough if I just go and	OSP, AS

		interview them and ask them. You really need to be there, work there, understand how they work, understand there day to day business to be able to set up these data models and to change ways of working to implement the right tools. Each department have to do that themselves, but with some coaching and guidance and help. A separate office is not good, but it's also good to have someone that drives it, that has the overview to see that we all are moving in the same direction. If you talk about tools or databases should be used or data structures, how should we collect it, how should we show it so that we all move in the same direction. So in that sense, it's good to have someone that takes control of it.	
41	OM	I understand, one of the things that also kept popping up is the inability of organizations to measure their progress and their success. I think when an organization is doing this transformation, then they can measure themselves, how can they measure their processes?	
42	R4	So I think one way is to as I said earlier, you need to have your data models. You have the table, you have this data, data models, and then see if you have data for all the things that you want to have data for. Then when you have that you have accomplished. I'm guessing that take will take years.	
43	OM	All right, so that that that's on the technical side. Do you think something should show on technical?	
44	R4	It's not technical, not technical at all.	
45	OM	Oh, but on the business performance, do you think there are some indicators that can maybe give a way that the chain is going in the right direction or not, like revenue or something?	
46	R4	No, I don't know about that. You should probably notice it in its efficiency.	
47	OM	OK, then the second last question is the importance of big data in an organization. How important do you think the availability of big data is?	
48	R4	It's super important!	
49	OM	OK, and do you think it is a requirement like if we say an organisation is not a data driven if it does not	

		use big data. Do companies always need to have big data to be data drive?	
50	R4	NO! to become data driven, you can use the data you have, but that data can soon become big volumes. We live in a world where everything is working with everything, we work with the whole globe. It's not just my company, I work with other companies, I work with the whole globe, you need to use more data to get meaning out of it. If you're a big company, you need to have big data.	
51	OM	OK, but that's quite understandable. Is there anything else that you think we might not have covered? What do you think organizations need to be aware of when implementing these data driven initiatives?	
52	R4	I think what people don't know and don't understand is you need to understand what type of data you want and knowledge about the data you're working with. Getting an understanding of that, helps to figure what attributes are around that. Then when I have that I try to get that data.	AS
55	OM	Let me just try to keep that in our analysis, we will anonymize the data that you've given us, and we'll also make sure that we don't include the company details. If you wish, we can share the transcript of the interview so that if you feel there's is an area where we might have misinterpreted you, we have an opportunity to correct it or if you feel like you need to re-emphasize something, you can do that with the transcript. But it might be a long document, so you're not really obliged to go detail by detail. Otherwise, we'll take more of your time.	
56	R4	I'm not that interested in the transcript. It's up to you to interpret what I'm saying, but I would like to see the thesis when it's done, if you could send it.	
57	OM	Yes, definitely. Ok, so that's fine, thanks a lot.	
58	R4	Thank you. Have a nice day.	
59	CS	Bye.	

Appendix F – Interview 5

Researchers: CZS = Conerlious Zecharia Sagandira (Lead Interviewer)
OM = Obey Mabaso (Transcriber)
Interviewee: R5
Work title: Project Manager
Date and time: 3 May 2021, 10:00
Transcribed by: Obey Mabaso
Checked by: Conerlious Zecharia Sagandira
Date of transcription: 4 May 2021

SEC	PERSON	TEXT	CODE
1	CZS	Hi R5, how are you doing?	
2	R5	I'm doing well, how are you, Cornelius?	
3	CZS	I'm fine. So as discussed before, I'm about to start our interview. The first thing before we start, I just wanted to ask your permission if we can record this interview. The thing that we really need to highlight is that we are not going to share personal details or company details of the people we interview. We will anonymize the analysis. Also, after our transcription, we will share the transcripts for you to confirm that we interpreted what you say correctly.	
4	R5	It's okay, you can go ahead.	
5	CZS	Can you please introduce yourself like your role and responsibilities in your organisation?	
6	R5	I am a project manager and my main responsibility at my work is to lead project delivery within my department and I also oversee the testing of prototypes.	
7	CZS	I will recap the background of our research. We aim to identify influential factors that can affect the implementation of data driven decision making in organisations. We are looking at the data driven decision making as the use of data in the decision-making and management. Noting that researchers before us focused on technological aspects, our intention is to focus more on non-technological or organisational factors that influences the implementation of data driven decision making.	
8	CZS	The first question is more in line with decision-making. What type of decisions have you mainly targeted	

		to support with your data? Do you target strategic or operational decisions or both?	
9	R5	I would say both. However, in my role, I mainly focus on project level decision which are short term and closer to operational than strategy. Strategic decisions are mainly taken at higher level, let's say my manager going up.	ODM SDM
10	CZS	Do you think you rely on data in these decisions?	
11	R5	Yes, definitely. There is a lot of data at work and it's used at all levels. We do use data a lot. Within my department we normally use it before we start with any project and we compare our historical data to make analogous estimates of new projects.	ODM SDM
12	CZS	In working with your data, have you felt the need to adjust your processes or the way your organisation or department is setup in order to be more suited to the data driven culture?	
13	R5	We have had to keep adjusting our ways to keep improving. We have projects focusing on changing the structure and the way we work in our organisation.	OSP
14	CZS	To what extent do you think this has helped you become data driven?	
15	R5	It has helped, to a greater extent, it kind of helped us to highlight the things that we needed to improve, so that actually helped a lot because it was a pointer for us to see where we needed to make corrections for the better and which frameworks to use in the near future to capture data and incorporate it as input to the process.	OSP
16	CZS	When relying on data to make decisions, who has the accountability? The decision maker or the system?	
17	R5	Well it depends. In automated decisions, the system or the system owners are accountable. However, most of our decisions still require human intervention and in this case it's the people who take accountability. It still remains a process in which different stages of the process requires different people to take responsibility. However, I believe to encourage the trust in data, we need to shift accountability to systems otherwise people will continue overruling what the data says.	OSP
18	CZS	Do you consider your organisation to have a data driven culture?	

19	R5	Yeah, yeah it does very much. We try as an organisation to ensure that everyone is on board before we start any projects so that we build the culture amongst employees. In our inclusive framework everyone has to contribute their ideas. The problem is that it can lead to longer decision-making times. The good thing is almost everyone in our organisation appreciate the role and importance of data in our decisions. So, at the end the decision is based on what ideas are supported by data.	OC
20	CZS	Thanks for that. So, moving on to the next question, that is the management support, what role does the management play in the implementation of a big data analytics or data driven organisation? Do you consider them a supportive or resistive?	
21	R5	I know they are very supportive of the data driven initiative. They want us in some way to reach the top so they are very supportive. Whenever we want to implement any technology, they always avail the required resources. Also, they are willing to take suggestions and ideas as long they are supported by our data.	MS
22	CZS	Okay, thank you. Yeah, that's nice. So, do you think this is or this had an impact on the success or failure of data driven organisation transformation?	
23	R5	That has greatly impacted, in a successful manner. The other thing is we don't usually look at the hierarchy. We work with our management as a team and this has helped a lot in progressing together as everyone’s input has a factor in our outcomes.	OSP MS
24	CZS	Okay, thank you for that. So, we are moving on to the next question. That is the availability of resources and skills. What skills do you consider mandatory in the implementation of big data analytics or data driven decision making?	
25	R5	There is still a gap in this area. We need data developers who also understand our type of work and the aim of our organisation. It is essential to develop employees already within the organisation as we need more skills in our group to help us develop.	AS BDA
26	CZS	So how prepared was your organisation skills wise?	
27	R5	Like I said, there is still a gap we need to close. We recognise the importance of skills in this	AS

		transformation. Advancing our skills can have a positive impact in our transformation.	
28	CZS	How much of your success or failure do you attribute to good or poor change management strategy? By change management, we are referring to a how you manage the changes introduced by data driven transformation to ensure minimal disruption to the way you work and bringing every employee is on board.	
29	R5	How we manage this change will have an impact. It does a lot because most of us struggle with adjustment. Adjusting the way you work and the people you work with takes time. Demands of management will change as well. So, it is important that we introduce this change properly.	CM
30	CZS	I see. Well, that was my last question. Do you think there are any other factors you need to share?	
31	R5	No, I think that's basically about it. You need to understand that my focus is on projects and my visibility to our decisions is from a project management point of view. Our organisation is big and the progress made might be different from department to department. But overall, that’s about it. If you need to know more, you can let me know if your schedule still allows.	OS
32	CZS	Yeah, I think that's enough for now. I thank you very much. I just to emphasise that we will not publicise any personal or company information. We will anonymise our results and analysis. Thank you.	
33	R5	All the best and have a great day.	

Appendix G – Interview 6

Researchers:	CZS = Conerlious Zecharia Sagandira (Lead Interviewer) OM = Obey Mabaso (Transcriber)
Interviewee:	R6
Work title:	User Experience Researcher Data Analytics
Date and time:	10 May 2021, 14:00
Transcribed by:	Obey Mabaso
Checked by:	Conerlious Zecharia Sagandira
Date of transcription:	11 May 2021

SEC	PERSON	TEXT	CODE
1	CZS	Hi, how are you?	
2	R6	I am great.	
3	CS	We would like to ask for permission to record this conversation for transcription purposes. We will not share the recording and we will anonymise our analysis meaning no personal or company information will be shared.	
4	R6	Go ahead.	
5	CZS	We can start with you introducing yourself, your role and what your company does.	
6	R6	Okay, yes, so my name is R6, I work for Company X and I'm employed as a senior user researcher. My role is to help the organisation to understand and describe the different customers and users that we are doing our data analytics product for. Everything from the kind of context that different people we are supporting with our product are in. Describing what these different people or groups of people are doing in their jobs that data analytics can help them with. At the moment we're focusing on enterprise organisations, big organisations where you will find a sort of a division of labour. As you would imagine, there are people who specialise in working with data, so they connect to systems and different data sources to give other people access to data. Then there are other people that are more specialised in looking at the data, analysing the data bringing out reports or analysis so that others in the organisation who don’t have time and skill can make use of data in decisions for example managers and executives. So, there are different groups of people, so I'm responsible to do a little of that that research.	OS

7	CZS	Thank you. I will recap the purpose of our research. We aim to identify influential factors that can affect the implementation of data driven decision making in organisations. We are looking at the data driven decision making as the use of data in the decision-making and management. Noting that researchers before us focused on technological aspects, our intention is to focus more on non-technological or organisational factors that influences the implementation of data driven decision making.	
8	CZS	What type of decisions do your clients target to support using data? Is it operational or strategic decisions?	
9	R6	I had say both. However, I cannot quantify how much of each. It depends on the client, some are more focused on operational while some are focused on strategic decisions.	ODM, SDM
10	CZS	On the scale of data, are you frequently working with Big Data or it's any form of data?	
11	R6	It depends with the client as well. When you look at big companies, they have serious amounts of data in data warehouses which requires a lot of transformation that is Big Data. On the other hand, smaller companies have less amount of data in some cases excel sheets. But you need some sort of data to be data driven.	OS, BDA
12	CZS	In your opinion, what are the organisational or non-technological factors that an organisation needs to consider when implementing data driven systems or decision making?	
13	R6	From my perspective, I'm a researcher and I'm also something we call a design thinker. There is a particular approach that I'm sort of focusing on when thinking about customer experience and user experience. You know companies want to be more efficient by bringing technology in different ways. Computers makes us smarter, makes us more efficient because computers can do a lot of work for us and help us in different ways as humans in organisations. But there is a tendency to focus too much on the technology platform. There is a sort of a figure on that, 84% of these digital transformations fail because there is this technology focus and sort of solving functional problems, and organisations take very long time to get to business value. So, on the other side, thinking about what value the technology brings is better, like growing the market or being more efficient as an organisation, making customers happier, being more insightful and taking better decisions with data for example. When adopting technology, focus must also be given to people who are going to use the technology. Their requirements,	PV, AS, OSP

		priorities, and skills. These must be people who make decisions like the executives or management. User onboarding must be customised. Some users require more data than others. Training packages must be tailored according to the users.	
14	CZS	Yeah, that that was quite informative. How important do you think the skills of the employees are in the successful adoption or implementation of data driven systems?	
15	R6	Yes, of course they need to have certain skills. Organisations need to educate their people and know for example with the data analytics and promote Data Literacy in the organisation. People need to understand the tools and the data. However, the required skills will differ depending on the job. If you choose to train employees, there must be different learning paths from department to department for example business vs technical people.	AS, OSP
16	CZS	How important is management buy-in or support in all that?	
17	R6	Ultimately, management support is required. I think it's super important and seeing that many executives are influencers or decision makers about what tools and what technology to adopt. But it's also very divided here. There are IT leaders or data leaders. There are maybe business leaders and executives. It's easier to have IT leaders become champions of adoption because of their experience with technology but all leaders need to be on board. So yeah, it's super important.	MS
18	CZS	Okay, thank you for that. Then on the structure and processes of the organisation, you mentioned that in some cases it might not be the same tool for everyone. Do you think there is any need to pay attention to how the organisation is structured or how processes are setup during adoption?	
19	R6	Yeah, yeah, absolutely. There is need for some transformation to suit the new way of doing things. Also, there is need for modification or maybe a change of mindset on how processes are supporting different people using different tools and data. So yeah, this is a very important aspect.	OSP, OC
20	CZS	You mentioned shift in mindset. How important is the organisational culture in data driven implementation?	
21	R6	I don't have statistics or examples to demonstrate this. But culture is an important aspect for an organisation to gain benefits out of a technology investment.	OC
22	CZS	Do you think how you implement Change Management is important? Why?	
23	R6	Yeah. I have worked in areas where there is a lot of change management going on but never led it myself. It's an area so	CM

		important that it is handled by experts in change management. If not done properly, the technology might fail to deliver value.	
24	CZS	We have covered basically all the themes we intended to cover. Do you think there any other factors you might need to add?	
25	R6	I said about companies being clear about the value they are looking for. Different groups of people are going to use data analytics and how to get that together. There needs to be a clear idea about how that ties into different process that are going to support people in using these different techniques. There might need to be a programme or committee that drives this in organisation that has the responsibility to be clear about this sort of mapping of value to different groups of people with different tools and so on. Making sure that as this is happening, there needs to be a buy in high level offices. Then I mentioned the need for different learning pathways for users depending on the role. Then there need to for data, Big Data or any data, but it has to be good data.	OSP, CM, MS, AS, PV
26	CZS	Yes. Thank you so much for setting aside your time to talk to us. We are going to transcribe the interview and no personal details will be shared.	
27	R6	Thank you and good luck.	
28	CZS	Bye.	

Appendix H – Interview 7

Researchers: CZS = Conerlious Zecharia Sagandira (Lead Interviewer)
OM = Obey Mabaso (Transcriber)
Interviewee: R7
Work title: Business Intelligence Developer
Date and time: 11 May 2021, 16:00
Transcribed by: Obey Mabaso
Checked by: Conerlious Zecharia Sagandira
Date of transcription: 12 May 2021

SEC	PERSON	TEXT	CODE
1	CZS	Hie, how are you?	
2	R7	I am fine, thank you.	
3	CZS	Firstly, we would like to ask for your permission to record this interview for our transcription purposes. We would also like to highlight that your name and company details will be anonymised.	
4	R7	Ok that’s fine, you can record.	
5	CZS	Ok thank you, so I will start recording now. Maybe you can start by introducing yourself, your role in your organisation and key responsibilities.	
6	R7	Yes. So my name is R7. I am currently working as the business intelligent developer and my job mainly focuses on analysing data and creating various visualisations to the business so they can make decisions based on data. So, it's a lot of creating various visualisations, reports and trends based on business needs.	
7	CZS	That's quite interesting. So, before we move on to the next section of the interview, I will recap our research aim. Our research aim is to identify the factors that influences the adoption and implementation of data driven decision making. By data driven decision making, we just mean using your data that you have as an organisation to inform your decision making, it could be using small reports or having a data warehouse and using sophisticated business intelligence tools. Also noting that the researchers that came before us, they focus mainly on the technological aspects of these factors. We are focusing on organisational factors, more	

		like non-technological factors, because technological factors have been already identified by other researchers.	
8	CZS	OK!, So, in your role as a business intelligence developer, you said you focus on informing the decisions that are made within your organisation. What type of decisions are you targeting, are they operational decisions or strategic decisions?	
9	R7	It involves both I would say. So, when it comes to an organisation, there are various departments. Some of them, for example, could be marketing and sales, who would be interested to see the return on investment on their marketing campaigns. Based on them, they want to strategize themselves for the next years or strategize themselves to the remaining part of the year. So, there is higher management who would want to see how each department is working at a bird's eye view to strategize everything. But then again, there could be like teams such as financial teams, who are more interested in day-to-day financial status, how are they performing on different products in different regions. For example, in my role, I have created various reports, dashboards for day-to-day operational level like to understand the existing business performance. So, I would say both.	SDM, ODM, MS
10	CZS	Interesting, on the data that you use, would you consider your organisation to be using big data or is just any form of data	
11	R7	The domain that I work is based on Small Medium Enterprises SMEs. We support clients like various companies to send messages, we call it A to P messaging. Then, because of that, we do have quite a lot of volume, for example, we would have like, 2 billion transactions per a month worth of data. But that's, quite a lot of data. We also have various different products, catering different end user requirements. So right now, we do have a data warehouse solution, as well as a data lake solution that captures the data processes and ultimately that gives us the data for reporting purposes. So, I would say yes, we have quite a lot of data, but I don't know, when it comes to big data. Big Data is like, the famous three Vs or four Vs or five Vs, I wouldn't see like ours reaching the extremes like	AS, IS

		social media level of data, where it's like the varieties like extremely variant, in our case, it's not that up to the variant level. But our company recently merged with different companies, they acquired different companies recently. With that, we got exposed to a lot of various different databases from different companies, exposing us to a lot of different data. So, in that scenario, we had quite a bit of different kinds of data. That's where the data lake came into the picture.	
12	CZS	So, you do you think big data is a requirement for an organisation to implement data driven decision making?	
13	R7	I wouldn't say it is a requirement, when you say data driven you, I would, in my opinion, have to have some quality data in a good enough volume for you to make sense out of it, I would say, if you have very little data and the quality is very poor, you can't really make any sense with that data. So for you to be ready to make decisions based on data. You have to have quality data with a good volume I would say. It's not exactly how much the large volume of data that you have, that matters, it's those two like it should be also very quality data. Then the organisation also should have a clear picture which areas or which business decisions can be actually made based on data. So that understanding also should be there within the organisation a clear objective, these are the business areas that we can create based on the data that we have.	PV BDA,
14	CZS	Okay, I understand, then, in your opinion, based on your experience working with data, if an organisation is implementing a data driven culture or trying to transition towards data driven decision making, what factors do you think they should focus on?	
15	R7	I would say to go data driven, first thing is that the company should have very clear goals, objectives for their business, like within this year or within this near future or like for the far future or like for this time period, we need to achieve these goals. So, they need to have like very clear goals first of all. Then they could have look at the quality and the value of the data that they have and see whether they can build insights out of that data that will help them to bring any information or insights that will help them to understand	AS, OC, PV

		whether they are going to execute a decision. So, not having a clear business goal objective mission is one of the key limitations. That's one factor that they should have like clear goals and visions. As I said, the second one is the quality of the data and the volume of the data is extremely important. Then they need to understand if they have the right people to implement the data driven solutions they want within the company or if they can consult from some other companies to do that for them. Because a company's core competency would not be to analyse data. They would be for example, if a company is creating some food, let's say like, my company is creating biscuits. We have a lot of data that we gather every day, but my employees core competencies are not to analyse data and bring in visualisations then that would be a problem for them to go towards data driven organisation, they need to have the right people to implement that for them.	
16	CZS	Okay, interesting that you mentioned, the data quality, the way we look at data quality, I think it's linked to the processes within the organisation. So, in this case, how importantly the processes of the organisation towards the implementation is influential in transforming into data driven to adjust their process?	
17	R7	I would say if the data quality is low, then yes, they need to reconsider how they are capturing the data from the source. Because there could be scenarios even if I have faced that kind of scenarios where some data for example, let's say it's the salesperson who personally goes and updates data in the database. If there is no clear process for them on how to update the data, then we'll get a lot of empty values or incorrect values inconsistencies in the values that they input. We can't really bring out a common visualisation to anybody that made in a way that it makes sense. So I'm currently facing that kind of an issue. There are like a lot of insights that want to see but the quality of the data is low, because it's a manual entry that is happening and the there's no common way of entering data. It's, not a defined process, everybody does in their own way and interesting, so I can't really do the visualisations the way that they want. So we have data but it's	OSP, OC

		not common, and we can't really transform that data to a way that it makes sense.	
18	CZS	I understand, and you also mentioned that your organisation has been in the process of acquiring new companies and I see a dynamic structure, in your organisation. How does that affect your job like the role of trying to inform decision making?	
19	R7	Well, that's how that affects our role. That's a really big challenge. So, they have their own visualisations that they have done within their companies. But once you acquire companies, the top management would want to see everything in a bird's eye view. Right now, the approach that we are taking is, we are letting the acquired companies to gather the data and store the data that they are doing their own ways. But we are trying to get like snapshots to export each month from each of these acquired companies and bring into a central place and try to transform into a one the somehow. So, sometimes in certain cases, we might be lacking certain data in certain companies, that's expected, like some companies might not have the exact same data that another company will have. But at least the main things like the gross profits, the revenues, the costs, you know, the main things that business would want to see, they are like mostly common across the companies, perhaps the products, the product variations, the client portfolios could be different. Those differences I know, I think, the management also knows about those things. So what we are trying to do is we are loving, at least, for now, we are loving those different companies to handle their data in that way. But we are trying to export the most common things together, which makes sense to the high management.	OSP
20	CZS	That's quite interesting. What role do you think the management play in successfully implementing data driven culture?	
21	R7	Yeah, I think they play a big role. So, first of all, as I said, the management are the ones who understands the existing business needs. So they need to communicate the business objectives, goals, as I said, to all the employees in a good way that everybody understands, to say this is the goal that we are trying to achieve. Then if they want to make decisions based on data, as	MS, CM

		I said, they need to understand if the company has the right people to implement the solutions that they want. So, as I said, that's why it's important for them to communicate the end goal where they want to go.	
22	CZS	That's quite understandable. But beyond the management, like in your organisation how is the organisational culture and do you think it's important for the organisation to create this culture of data driven?	
23	R7	Yeah. So, I think, once they have the right data in their hands, I have seen most employees they appreciate it. I have never seen employees like ignoring once we create, like a good report, or visualisation for them, because it gives them a certain certainty on the current situation. For example, if you're going with for a certain region with negative margins, and if that had been a trend for some time, they would be absolutely interested to see that. Then it brings out conversations within their teams to understand why, like, what's the story behind it, why it has been negative margin for so long? So, I think culture is something that needs to be considered as well.	OC, AS, OSP
24	CZS	Okey, so beyond the people, you mentioned the importance of skills of having the right people to implement the solutions. Do you think it's important for everyone in the organisation to have at least some level of skill to work with data?	
25	R7	I would say that's absolutely necessary for everybody to have the skill to handle data. It would be a good skill to have as a person, but it's not a must skill to have. For example, if I am from marketing team, and if I'm looking into reports, or dashboards, which shows me data driven information. I don't need to understand how the backend things work or how the data works, that's not my duty. But I think it's more towards the data team to create dashboards, that makes sense to the end user. So, it's their job, it's their responsibility as experts in creating the dashboards that bring sense to the end users. Then it's also up to the data team to build those dashboards or build those reports to the end users. So, the end users can use them with minimum training. When you look at it, it should give you the right insight you want to see. So, I wouldn't say everybody needs to have the skill to handle data.	AS, OC

		They should just have the attitude or the keenness to use the data in their decision making and I haven't seen a lack in that department.	
26	CZS	Which is perfect. Then, on the type of decisions, we mentioned earlier that you use data to drive both operational and strategic decisions. I have you seen any defining success levels? To say maybe you can say you've had more success in implementing operational decisions more than strategic decisions, or they're all it's 50/50?	
27	R7	Yeah, it's a 50/50. So, I wouldn't say this one is more important than that one. So, I would say both are equally important. So operational level dashboards we are giving them the day-to-day business decisions. At a really high level, it would be like strategic decisions. So, the strategic ones are important for your future and for the continuity of the business in in like for the longer term, but the operational ones are important for the continuity in day-to-day level. So, both are important.	SDM, ODM
28	CZS	Our second last question, we have noted that introducing a data driven culture introduces a lot of changes within the organisation, if you are keeping on changing, how have you managed this change and making sure that it goes well with the users downstream?	
29	R7	Yeah, so I would say, it was a bit challenging when I joined the company, I created dashboards and that gave them a lot of a lot of problems around them to first trust the data because for a decision to be made solely based on data, they need to trust the data first. So, that's one department or one topic that is challenging, how are you going to make use of trusted data, is this the right data, are these numbers correct, this gives you the right picture of what you are supposed to work with. So, building that trust is the challenge, I would say. Then once you build the trust, then comes all sorts of requirements to say does that help the business goal? So, the next challenge would be like when a lot of requirements coming from different employees understanding or filtering out the exactly the best ones to be implemented. Because the end users are not experts in data driven insights, right. They are experts in their day-to-day operation or whatever, a marketing	CM, AS, BDA, OC

		person would be expert in marketing and salesperson would be expert in sales and finance or finance. They look at numbers on day to day, but they are not the experts in showing that data in a good way. So when requirements come in, it will be very challenging to filter out which requirements actually caters all that. So, identifying that is super challenging situation.	
30	CZS	Yeah, that's quite interesting. Change is a difficult thing to work with.	
31	R7	Yeah, it is. If there was like a legacy system implemented. If you're switching to a different kind of solution, of course there is the common issue of users not happy with changing the systems. So that's also a challenge. If you're switching or developing different solutions. That's common everywhere for any solution, I think.	CM
32	CZS	Before we end this, do you think that there are any other factors that we might have missed in our discussion that you think are important?	
33	R7	I think we've touched upon the main things. There could be various or depending on the company that you work on the domain that you work. But for example, I haven't faced so far a situation where I have to work with extremely different data varieties like video, audio, image, and all that kind of things. If I was in that kind of area, then I would have like, more different set of drivers or factors or problems, I would say. But the ones that I have highlighted are towards the domain that I work in.	IS
34	CZS	I just got a reminder from Obey on company size. So what do you think does it affect the way the approach you take when implementing data driven?	
35	R7	Oh, well, I wouldn't say it matters. What matters is the quality of the data and the volume of the data. Having good objectives, as I said, even for a small company, if you have like good amount of quality data, you can bring out good insights. So I wouldn't say in my opinion, I wouldn't say the company organisation size would matter.	PV, AS
36	CZS	Okay, yeah, that's understandable. If these nothing else, I think let me take this opportunity to say thank you so much for talking to us. That was quite informative. We really appreciate your time.	

37	R7	It's a pleasure to work with having this interview with you guys. I wish you good luck with the thesis and the final submission	
38	CZS	Thank you, bye.	

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